Trade Disruptions Along the Global Supply Chain*

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Abstract

In 2020, a pandemic generated by a new pathogen caused the largest and most abrupt monthly decline in world trade in the last half-century, when consistent records began. That collapse followed naturally due to the difficulty of continuing locally producing, transporting and consuming goods in the affected regions worldwide. In this paper, we study the impact of these local disruptive shocks on international trade flows during the COVID-19 pandemic. Using rich product-level import data from Colombia, we show that in aggregate, import collapse at the onset of the pandemic was due to a decrease in import quantities, and the import recovery in later periods was partially explained by a rise in foreign export prices and shipping costs. We then study the impact of local human mobility declines on imports, including the mobility declines experienced in exporter cities, ports, and importer cities. We find that the average decline in importer mobility lowered imports by 11%, and the average decline in exporter mobility did so by 3%. Using data on port calls made by container ships, we document a decline in port productivity during the pandemic. We show that mobility changes at port locations induced a decline in port efficiency and a rise in freight costs. Using a trade model in which local exporters produce different varieties, we show that most of the decrease in import values at the outbreak of the pandemic was due to local demand-side shocks. We also document a positive correlation between goods-level national inflation and local mobility shocks to foreign exporters.

Keywords: International trade, local shocks, COVID-19 pandemic, shipping costs, mobility, supply chain, inflation.

JEL codes: F10, F14, F16, I12, O18.

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1 Introduction

The flow of international trade depends on the ability to produce, transport, and consume goods at different locations. The Covid-19 pandemic generated disruptions in all three aspects. On the one hand, production capability was compromised by containment efforts, illness, and shifts in workers' preferences. On the other hand, the transportation sector was hit by similar issues, and also suffered from potential congestion when unprecedented volumes of goods needed to pass through ports with limited capacity. Finally, the demand for goods was likely affected by changes in present and future expected income, work modalities, and shifts in consumers' preferences.

In this paper, we study the impact of local disruptions at different points of the supply chain on international trade. We exploit a rich dataset on Colombian monthly imports by 6-digit HS product, exporter location, and importer location with detailed information on import quantities, import prices, export prices, and the wedge between the two, shipping costs. First, we document changes in trade and transportation variables over the pandemic. Second, we combine information on the location of the exporter and importer with local changes in mobility to estimate the direct impact of disruptive shocks on the quantity and prices of goods imported by Colombia. Third, we estimate the impact of disruptions to the transportation sector by using the port performance and port-specific mobility declines, both in terms of direct labor cost increase and in terms of congestion. With the help of a simple theoretical framework, we next decompose the impact of the pandemic into exporter, importer and transportation shocks. Finally, we link local disruption shocks to the rise in inflation observed during the pandemic.

Colombia offers a unique opportunity to study the impact of local trade disruptions during the pandemic. First, it is a small economy in world trade. Therefore, changes in local mobility in foreign countries are not likely to be impacted by the demand and supply of goods in Colombia. Thus, it is reasonable to assume that the foreign mobility shocks are exogenous to Colombian imports. In addition, changes in Colombian demand are unlikely to generate shipping congestion in foreign ports for the same reason. Second, Colombia is integrated into international supply chains, with an average import penetration in manufacturing sectors of about 60% before the pandemic. Therefore, Colombia provides an ideal laboratory to study the consequences of the pandemic on international trade.

We exploit variation in local Covid outbreaks and human mobility in different regions across the world and in time to identify the impact of local disruptions on international trade. This is likely to be the case since the spread of the disease and behavior responses vary substantially across countries and regions and over time.

Our paper uses highly granular data on mobility, trade flows, and maritime transportation. Our trade outcomes are monthly trade information collected by Colombian customs. The data allows us to identify exporters and importers at the city level (or city-equivalent level). To measure shocks to local producers and consumers, we use changes in human mobility to measure local disruptive shocks during the pandemic. We obtain monthly changes in mobility in Colombia and its 27 major trading partners' cities from Facebook and Baidu and match the exporter and importer cities with their mobility changes. Changes in mobility are measured relative to the pre-Covid period, and we use them to proxy for the decline in local economic activity across regions. Finally, we obtain the universe of port calls made by container ships in these exporting countries from January 2019 to October 2021 to measure port performance. We observe the number of port calls, total ship capacities served at the ports, and the number of hours each ship spends at the ports. Importantly, the number of hours in port can be used to measure port efficiency.

We start by documenting trends in trade during the pandemic. Colombian imports experienced a 40% initial decline, explained mainly by a collapse in import quantities, and subsequent recovery. Export prices remained relatively constant until the first quarter of 2021, when they started rising to reach an increase of about 12% above pre-pandemic trends in October 2021, the last month we include in the analysis. Shipping costs steadily rose since September 2020 and reached an increase of 70% in October 2021. Overall, import prices were 18% above pre-trends in October 2021, with shipping costs directly contributing 40% to that increase.

We find that both reductions in mobility at the exporter and importer locations during the pandemic caused product-level import values to decrease. In our preferred specification, the average importer mobility reduction lowered imports to that location by about 11%, whereas the average reduction at the exporter location decreased imports by 3%. In order to guide our empirical strategy, we employ a simple theoretical framework in which importers imperfectly substitute across varieties produced at different locations, and exporters charge monopolistic prices and have short-run decreasing returns to scale. Consistent with this setting, we find that importer mobility shocks acted as demand shifters, explaining all their shock to import values. Negative exporter mobility shocks decreased import quantities but increased import prices, partially explaining the lower impact of local disruptions at the exporter location on import values.

We also observe salient trends in port performance across the world. In 2020 and 2021, world trade was about 5-10% below the 2019 level and did not fully recover even by the end of our study period, in October 2021. This pattern holds when we use the total number of port calls or the total ship size in 150 ports across 27 countries used in our study. In addition, the average hours in port experienced a steady increase since July 2020, with an about 25% increase in October 2021 compared to October 2019. This suggests that port productivity declined substantially during the period, with fewer ships being processed and longer delays in processing time at ports.

We then use the mobility changes in port cities, optimal shipping routes, and changes in freight costs to investigate the impact of the pandemic on sea shipping. We find that an average change in mobility induces a 2.2% increase in the hours in port at the exporting country. Furthermore, this change in mobility in the exporting country's ports also translated to a 4% increase in freight cost, and the elasticity of mobility to freight cost is even higher for intermediate countries.

In addition, we find that 2021 had a larger number of hours in port and a higher freight cost than 2020, even after controlling for mobility changes. This is likely to reflect the accumulated effect of the pandemic through disruptions in trade patterns across the world and disruptions in domestic transportation services, such as shipment by trucks.

We employ the theoretical setting and baseline empirical results to decompose the pandemic impact into exporter, importer and transportation shocks over the pandemic. We find that 67% of the total impact on import quantities at the onset of the pandemic was explained by disruptions at the importer location, 26% was explained by disruptions at the exporter location, and the remaining 7% by disruptions at ports. In terms of import prices, all the initial increase was explained by disruptions at the exporter location. Towards the end of our sample, most of the decrease in import quantities and increase in import prices were explained by the linear increase in transport prices not directly related to disruptions.

Finally, we explore the relationship between local disruptive shocks at the location of exporters and goods-specific inflation. We find a positive relationship between the increase in import prices due to exporter mobility shocks and the increase in consumer prices of goods included in the Colombian Consumer Price Index for which we observe positive imports. Results suggest an immediate and direct pass-through from local foreign shocks to consumers of about 60%. The total observed pass-through from import prices to consumer prices is 1%, suggesting the existence of mitigating factors.

Our paper contributes to the literature on the impact of local shocks on firms and trade. Researchers have documented the impact of natural disasters on trade, e.g., how an earthquake disrupts domestic roads to ports and affects exporting activities (Volpe Martincus and Blyde, 2013). In addition, these effects also propagated along the supply linkages (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). There is also direct evidence on how input shortages (e.g., electricity shortages) dampen firm growth (Allcott et al., 2016). We contribute to this literature along several dimensions. First, we study a plausibly exogenous shock that affects regions across the world differentially, and we show how shocks to one country and one region propagate globally through international trade. Second, we have a direct measure of the size of the shock across regions, which allows us to estimate the elasticity of trade with respect to the shocks. Third, we have detailed information on price, quantity, and freight costs to estimate the impact on trade along different margins. Finally, we decompose the overall changes in trade outcomes into the impact of importer shocks, exporter shocks, and port shocks.

Our paper is closely related to the literature on the role of transportation in trade, especially new literature on maritime shipping. In two recent papers, by Heiland et al. (2019) and Ganapati et al. (2021), the authors use container ship port call data to measure the global maritime shipping network and estimate the impact of changes in certain nodes in the network on global trade and welfare. Related, Cosar and Thomas (2021) find substantial regional welfare losses in the event of the closure of key maritime waterways in Southeast Asia. We contribute to the literature in three ways. First, we focus on a different type of shock to maritime shipping: the labor shortage at port cities. Second, although we also use container ship port call data, our objective is not on shipping routes. Instead, we construct a novel measure for port productivity. We use the number of hours each container ship spends in the ports to capture port efficiency, and document how local labor shocks can reduce port productivity. In addition, we have the measure of the number of port calls and the number of hours each container ship spends at the ports around the world over multiple years, allowing us to document the changes in port performance. In contrast, the aforementioned two papers use a cross-section. Third, we have direct measures of freight costs, and we show how shocks to ports push up freight costs.

The international trade literature has traditionally modeled transport costs as an exogenous iceberg cost. However, early work by Hummels and Skiba (2004) showed that shipping prices are positively correlated with export prices. In light of it, recent papers endogenized the international transport sector by stressing the role of round-trips (Wong, 2018), networks effects (Brancaccio et al., 2020), and price discrimination (Ignatenko, 2020) for shipping prices and their impact on trade. We contribute to this literature by showing that shipping prices also react to local shocks at ports, providing further evidence of its endogeneity.

Our paper also relates to the literature on the short-run impact of changes in the trading environment. Anderson and Yotov (2020) show that the short-run trade elasticity is one-quarter of the long-term due to fixed bilateral capacities. We use this idea to construct the theoretical framework, where production has decreasing returns to scale, and shipping has limited capacity. We also decompose the short-run impact of changes in trading conditions as in Fajgelbaum et al. (2020), which find that the tariff hikes due to the U.S.-China trade war reduced imports and exports in the short-run entirely through quantities. In our setting, quantities and prices react differentially depending on the location of shocks.

Finally, this paper contributes to recent research studying the impact of the pandemic on trade and economic activity in general. First, a few papers develop quantitative models to simulate the impact of country-level pandemic shocks on supply-chain disruptions (Guan et al., 2020; Bonadio et al., 2021; Liu et al., 2021). Second, several papers document the impact of the pandemic on labor markets and on income and consumption (Chetty et al., 2020; Coibion et al., 2020a,b). Third, some papers develop general frameworks to study the impact of globalization where trade also spreads diseases through human interactions (Antràs et al., 2020), and the impact of an increase in trade in services due to the offshorability of remote work (Baldwin and Freeman, 2021). One exception is Martin et al. (2021), where the authors show how French firms sourcing from Chinese experienced declines in exports in the early period of the pandemic. Lastly, (Khanna et al., 2022) employ variation in lockdown stringency across Indian districts to characterize supply chain resilience at the firm-to-firm level. To the best of our knowledge, we are the first to use detailed measures of *actual* trade outcomes, port performances, and human mobility at the sub-national level to causally estimate the impact of local pandemic shocks on international trade.

The rest of the paper is organized as follows. Section 2 introduces the data and presents trade, transportation, and mobility changes during the pandemic. In Section 3 we first present a simple trade model and then outline our empirical strategy. In Section 4, we study the relationship between exporter and importer local mobility shocks and Colombian imports at the product level. In Section 5, we study the impact of mobility and congestion in world ports on freight unit values. In Section 6, we present results on the decomposition of the pandemic effects over time. In Section 7, we relate the local disruptive shocks to Colombian inflation. Section 8 concludes.

2 Data and Motivating Facts

In this section, we present the different data used in the analysis, show their variation across different dimensions such as time and locations and present the most salient aggregate impacts of the pandemic.

2.1 Trade Data

In this section, we characterize monthly changes in Colombian import trade variables from 2018 to 2021. To do so, we employ data collected by the Colombian customs office and made available by DANE (the National Administrative Statistical Office by the Spanish acronym). This dataset includes monthly information about the importer location, exporter location, 6-digit HS products, import values, quantities and weights, and freight and insurance costs. For the analysis, we select the 27 major exporting countries to Colombia and the top 60 Colombian municipalities in terms of 2018 imports—which accounted for about 90% and 99% of total imports respectively in 2018.[1]

We start by documenting total monthly imports over the 2018–2021 period in terms of pre-pandemic averages. To do so, we take the month-specific average total import value of 2018 and 2019 in US dollars and use them to demean 2018-2021 imports. Figure 1 plots the demeaned values in million US dollars.

Before the pandemic, aggregate imports did not show large monthly swings, with changes always lower than 6% relative to the month-specific 2018–2019 average. Aggregate imports to the selected countries declined by almost 40% — 1.4 billion US dollars — at the beginning of the pandemic, and they increased by as much as 35% — 1.2 billion US dollars — during 2021.

These values mask the different underlying changes that took place in terms of quantities, export prices, transport costs, and import prices. In order to characterize the change in these variables, we aggregate the data to the exporter location, importer location, product, and month level to accurately define quantities and prices and reduce compositional changes. We define the exporter and importer location at the level at which we match the trade data to the mobility data, as shown in Appendix Table A1.

We decompose log import values m as follows:

$$m \equiv q + p^X + \tau \tag{1}$$

where q is quantities, p^X is export prices, measured in free on board (FOB) terms, and τ is the ad-valorem trade costs, which include both freight and insurance costs. Log import prices are measured in cost, insurance and freight (CIF) terms, i.e. $p^M \equiv p^X + \tau$.

We calculate each variable in Equation 1 at the exporter location (i), importer location (j), product (k), and time level at the monthly frequency (t) for the 2018-2021 period. In order to characterize average changes over the pandemic, we estimate the following equation:

$$m_{ijkt} = \sum_{r=01/2020}^{10/2021} \delta^r \times \mathbb{1}\{t = r\} + \delta_{ijkm}^{seas} + \delta_{ijk}^{trend} \times t + \varepsilon_{ijkt} \tag{2}$$

where m can be imports or any of the other variables in Equation 1. We include an exporter-

[1] We do not use all exporting countries because within-country exporter locations required extensive cleaning.

importer-product-month fixed effect δ^{seas} to control for granular seasonality, and an exporter-importer-product-specific linear time trends δ^{trend}. The coefficients of interest are the δ^r, with r ranging from January 2020 to October 2021. We interpret each of these coefficients as the average deviation from pre-pandemic trends at month r.

Figure 2a shows that the profile of average changes in import values over time was similar to the aggregate: a sharp decrease at the beginning of the pandemic and a slow, non-monotonic recovery. This pattern is explained mostly by changes in the quantities imported, as seen in Figure 2b.[2]

Export prices had a different dynamic. They remained relatively unchanged during 2020 and the first quarter of 2021 but started rising in the second quarter (Figure 2c). Ad-valorem transport costs increased steadily since the beginning of the pandemic (Figure 2d). In summary, quantities explain most of the changes in import values, and export prices showed relative upward rigidity up until the second quarter of 2021 but not afterwards. Transportation costs started rising early in the pandemic.

Trade costs in ad-valorem terms are the standard approach in the trade literature, but we can actually construct freight and insurance unit values, which help us analyze their changes independently from import variables. In Figure 2 Panels (e) and (f) we show their dynamics using also Equation 2 specification.[3]

Figure 2e shows that freight unit values increased more than 10% during the June-July 2020 period—right after some developed countries started relaxing lockdown measures. However, they began a monotonic increase in October 2020 to reach an average increase of almost 75% in October 2021.

Insurance unit values show a different pattern. As shown in Figure 2f, they remained relatively unchanged up until the beginning of 2020, showing, if something, a downward trend. In March 2021, they started increasing, reaching an increase of about 12% in October 2021.[4]

Export, transportation and insurance prices showed an increase over the 2020–2021 period, which means that import prices also increased, as shown in Figure B2.

What was the contribution of transportation costs to such an increase over time? We employ the following first-order decomposition to measure it:

$$\hat{p}^M = \theta^X \hat{p}^X + \theta^F \hat{p}^F + \theta^I \hat{p}^I, \tag{3}$$

[2]Import quantities are defined at the 6-digit HS level and do not change over the sample period, which means that, given the fixed effects in equation 2, coefficient estimates are well-defined.

[3]Specifically, we construct freight unit costs as $p^F \equiv \frac{\text{Freight total costs}}{\text{Quantity shipped}}$, and insurance costs p^I similarly.

[4]Note that March 2021 saw the Suez Canal Blockage, which reportedly increased losses of global reinsurers. See `www.fitchratings.com/research/insurance/suez-canal-blockage-large-loss-event-for-global-reinsurers-29-03-2021`.

where $\hat{\cdot}$ are differences with respect to pre-pandemic trends, and θ^X, θ^F and θ^I are the average pre-pandemic share of export prices, freight, and insurance unit costs respectively.[5] We then replace each term with the corresponding estimated deviation from pre-trends estimated in equation 2. Figure B2 shows that freight and insurance cost contribution to the increase in import prices was close to 50% towards the end of 2021.[6]

In conclusion, import variables experienced large swings relative to the pre-pandemic period. Import quantities declined and stayed below pre-pandemic trends, whereas import prices and their components increased steadily although with different timing. In the subsequent section, we will systematically study how the local disruptions generated by the pandemic affected each of these import variables.

2.2 Container ship port call data

We use port call data on 150 ports in 27 countries and regions from January 2019 to October 2021 to measure port performance. The data on container ship movement is from IHS Markit's Maritime & Trade Platform.[7] The platform collects and processes AIS (automatic identification system) data on ship movements of over 220,000 ships of 100 gross tonnages and above around the world. The 27 countries include 25 countries and regions that are top trade partners with Colombia (excluding Switzerland and Bolivia, which are landlocked, and Venezuela for which there is no mobility data), Colombia, and Singapore (as an important intermediate port). We include the most important ports in these countries. The 150 ports have at least 10 port calls made by container ships per month in 2019, and at least 5 port calls in each month in 2019. We focus on container ships as in Ganapati et al. (2021) and Heiland et al. (2019), since containerized seaborne trade makes up the majority of world trade on merchandise. The list of ports and their 2019 capacity is shown in Appendix Table A2.

Figure 3 presents the important trends in port performance from 2019 to 2021. Panel (a) shows the total number of port calls. We can see that the container ship trade was at a lower level in 2020 and 2021 than in 2019. The first half of 2020 had an about 10% decline, and the second half of 2020 experienced some recovery. The recovery continued until May 2021, and since June 2021, the number of port calls was even below the 2020 level. Panel (b) presents a similar trend, by measuring trade volume using the total twenty-foot-equivalent units of the ships that made port calls.

Panel (c) presents the trend in the average hours in port. The number of hours in port

[5]The average pre-pandemic export prices share in import prices was 92%, freight unit costs were 7% and insurance costs were 1%.

[6]Contribution is calculated as $(\theta^F \hat{p}^F + \theta^I \hat{p}^I)/\hat{p}^M$.

[7]See `https://ihsmarkit.com/industry/maritime.html`.

is measured using the difference between the sailed time and the arrival time for the port call. Arrival time is the first AIS position that appears within the designated port zone, and sailed time is the first AIS position recorded that appears outside of the port zone. Thus, the number of hours in port can measure the efficiency of port services and proxy for port congestion. Intuitively, labor shortages in the port can increase the processing time, and ships will need to spend more hours in the port. We can see that while the number of hours in port was very stable in 2019, it experienced a steady increase since July 2020, with an about 25% increase in October 2021 compared to October 2019.

Panel (d) presents the trend in the share of port calls whose last port call was made in China. In 2019, the average share was around 22%. The first four months of 2020 experienced a decline, since China experienced the initial Covid-19 outbreak and imposed strict mobility restrictions. The share started to pick up in May 2020 and continued to rise until June 2021. The timing of the decline in 2021 coincided with the decline in the total number of port calls.

In sum, the world maritime trade was impacted by the pandemic and port congestion became more severe over time. In addition to the aggregate trends across the ports, Figure A1 confirms the increase in the number of hours in port in some of the largest ports around the world. One of the most famous incidents was in the Los Angeles Port (Panel i), where the number of hours increased from about 75 hours in 2019 to more than 100 hours in 2021 and peaked in September 2021.[8]

2.3 Mobility Data

Countries around the world experienced declines in mobility during the pandemic, because of government restrictions, sickness, and voluntary containment efforts. We measure the local shocks in cities using the change in daily log mobility, where the baseline is the same day-of-week in the pre-Covid mobility. For China, the data is from Baidu Mobility Map, and the baseline period is the first two weeks in January.[9] The Baidu mobility measure captures the extent of within-city movement, by using the indexation of the share of people who leave home for at least 500 meters for more than 30 minutes. For Colombia and its 27 major trade partners, the data is from Facebook, and the baseline period is February 2020. Venezuela does not have Facebook data.[10] The Facebook data uses the location information of users who enable location services on their mobile Facebook app to measure the change in the log average number of 0.6 km squares visited during a day. The data is available at the

[8] See more about the Los Angeles port congestion here: `www.wsj.com/articles/why-container-ships-cant-sail-around-the-california-ports-bottleneck-11632216603?mod=article_inline`.

[9] Source: Baidu Mobility Map at `https://qianxi.baidu.com/`.

[10] See `https://dataforgood.facebook.com/dfg/tools/movement-range-maps`.

second-highest administrative level, so we refer to the regions as "cities." Only cities with more than 300 users are included. Then we average across the working days in a month (i.e., Monday to Friday) to measure the mobility change in a month.

Figure 4 presents the changes in mobility in Colombia and some of its major trading partners. For the exporting countries, the trend is the average mobility change across all cities that export to Colombia and have mobility data. The biggest decline in mobility happened in April 2020 when many countries imposed lockdown. Over time the mobility recovers, but not at the same rate across countries. For example, the mobility in Spain did not recover to the pre-Covid period even in October 2021. In contrast, South Korea experienced a fast recovery and had a level of mobility higher than the pre-Covid period in almost all months since April 2020. Colombia also experienced a large decline in mobility in April 2020, and had a rather steady increase over time.

In addition, there is substantial within-country variation in mobility. In Figure 6 we take Europe as an example and show the distribution of mobility declines across the eight European countries included in the analysis in September 2020. Overall, Spain and the UK had larger mobility declines than Germany and France. However, within each country, regions experienced differential declines as well. Similar variations can be observed in other countries, such as the U.S., China, and Mexico as shown in Figures in Appendix A.3.

Figure 5 presents the local mobility variations in Colombia in September 2020. Note that Facebook covers only 530 out of 1,065 *municipios* in Colombia. In Appendix A.4, we present the level of aggregation in each country and the number of units per country.

3 Trade Framework and Identification

In this section, we estimate the impact of local changes in human mobility on Colombian import variables. To do so, we first construct a simple trade model to guide our empirical strategy. Second, we detail our empirical strategy to identify the impact of the pandemic-related shocks at the exporter and importer locations. Finally, we present our baseline results and main robustness checks.

3.1 Theoretical Framework

We assume there are I locations in the world distributed in countries indexed by $c \in C$. Each location i has two types of firms. The first one produces products indexed by $k \in K$, where K is the industry. The second set of firms are competitive bundlers that sell industry goods domestically to either consumers or domestic firms.

Producing firms combine local labor and capital with a Cobb-Douglas technology to produce, where $\tilde{\alpha}_L^K$ is the labor share parameter. We assume that capital is fixed in the short run—the time frame we assume for the model. Given that we focus on their international trade activity, we call them "exporters". We use the index ik to identify an exporter located at $i \in c$ exporting product $k \in K$.

Bundlers' technology is also Cobb-Douglas and combine labor and the sourced product k to domestically sell it. They can source product k from locations in a pre-determined set Ω_{jk}^K, where j indexes the location of this firm as a buyer importing product k. Importantly, we assume that bundlers cannot perfectly substitute across locations, i.e. their production function is CES with an elasticity of substitution η^K over $i \in \Omega_{jk}^K$ varieties. We call these firms importers given our focus on international sourcing.

International trade is subject to a per-unit international transport cost t_{ijk}. Therefore, the import price p_{ijk}^M is equal to $p_{ik}^X + t_{ijk}$, where p_{ik}^X is the export price.

3.1.1 Local Import Demand

Import demand of product k from i at location j is given by the standard constant elasticity of substitution (CES) demand function:

$$q_{ijk} = (p_{ijk}^M)^{-\eta^K} (P_{jk}^M)^{\eta^K - 1} Z_{ijk}^K \tag{4}$$

where $P_{jk}^M \equiv [\sum_{\Omega_j^{JK}} (p_{ijk}^M)^{1-\eta^K}]^{\frac{1}{1-\eta^K}}$ is the CES price index over locations, and Z_{ijk}^K is a good K-specific demand shifter. This term can include a variety of factors. First, it can capture a decline in current and future expected income. For instance, we would expect a decline in quantities imported if a local disruption event increases layoffs—the bundler would see the demand for its goods reduced. We call this an "income effect". Second, it can capture a "substitution effect" to or from other goods—e.g. non-tradable goods. In this case, the impact of the pandemic can be either positive or negative depending on substitution patterns. Finally, it can also capture shocks to preferences.

3.1.2 Local Export Technology

We assume exporters have a fixed amount of capital over the period we consider, which means that, given their Cobb-Douglas technology, their cost function is:

$$C_{ik} = A_{ik}^K Q_{ik}^{\alpha^K} \tag{5}$$

where A_{ik}^K is a cost-shifter specific to good K, $Q_{ik} \equiv \left[\int_{\Omega_{ik}^{IK}} q(j)_{ik} dj \right]$ is total production, Ω_{ik}^{IK} is the set of locations served by i, and $\alpha^K \equiv 1/\tilde{\alpha}_L^K > 1$ captures the degree of decreasing returns to scale in the short run due to fixed capital. The cost-shifter A_{ik}^K can capture different factors, as in the case of demand. First, it can capture local changes in wages, which may have increased if the pandemic reduced the local labor supply. Second, it can capture changes in productivity, for instance, due to work-from-home patterns induced by the pandemic. Finally, it can also capture idiosyncratic supply shocks.[11]

3.1.3 Export Prices

Exporters maximize profits by choosing export prices given the CES importer demand and their technology.[12] Therefore, they charge the following optimal export price:[13]

$$p_{ijk}^X = \frac{\eta^K}{\eta^K - 1} \alpha^K A_{ik}^K Q_{ik}^{\frac{\alpha^K - 1}{\alpha^K}} + \frac{1}{\eta^K - 1} t_{ijk} \tag{6}$$

This expression captures different features of export prices. First, they increase to all exporters in the short-run if there is an increase in demand from any importer. Specifically, as exporter i faces more demand, the marginal cost of production $\alpha^K A_{ik}^K Q_{ik}^{\frac{\alpha^K - 1}{\alpha^K}}$ increases, raising the average cost of serving any destination. Second, cost shocks to location i also increase prices through A_{ik}^K (e.g. labor shortages that increase local wages). Finally, an increase in transportation costs also raises export prices because it shifts the demand curve inwards, decreasing marginal revenue.

3.1.4 Transport Prices

We assume the transportation sector is operated by a global firm that faces local decreasing returns to scale. The supply curve to ship products from i to j is given by:

$$t_{ij} = B_{ij} v_{ij}^{\beta} \tag{7}$$

where v_{ij} is the total volume of goods transported from i and j and $\beta > 1$ is the local decreasing returns to scale parameter.

Depending on their volume, different products face different per-unit transport costs. For instance, large products such as cars face a higher per-unit cost than smaller products such as shirts. To capture these differences, we employ a constant product-specific factor ρ_k, which adjusts differences in size: $t_{ijk} \equiv t_{ij} \rho_k$.

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[11]Given the technology assumptions, $A_{ik}^K \equiv \left[\frac{w_j}{a_j^K \bar{H}^{1-\tilde{\alpha}_L^K}}\right]^{\frac{1}{\tilde{\alpha}_L^K}}$, where a_{jk} is a Hicks-neutral productivity parameter and $\hat{H}$ is the fixed amount of capital.

[12]Exporters maximize $\Pi_{ik} = \sum_{\Omega_{ik}^{IK}} p_{ijk}^X q_{ijk} - C_{ik}$ by choosing p_{ijk}^X.

[13]See derivation in the Appendix C.1.

3.1.5 Solution in Changes

We are interested in how changes in underlying conditions affect equilibrium import and transport prices and quantities at the exporter-importer-product level.

We differentiate local import prices to get the following expression in changes:

$$\hat{p}^M_{ijk} = \iota_{ijk}\hat{A}^K_{ik} + \iota_{ik}\frac{\alpha^K - 1}{\alpha^K}\hat{Q}_{ik} + (1-\iota_{ijk})\hat{B}_{ij} + (1-\iota_{ijk})\beta\hat{v}_{ij} \tag{8}$$

where $\hat{.}$ means the log-change of variable x with respect to the equilibrium value, and $\iota_{ijk} \equiv \frac{p^D_{ik}}{p^M_{ijk}}$, assuming that transport costs of shipping to the domestic market—where the exporter is located—are zero and thus the domestic price p^D_{ijk} is determined only by the local marginal cost of production and producer markups. As expected, import prices increase when exogenous production costs rise, but also when the total production increases, given that the marginal cost increases through congestion in the short run. Finally, an increase in transportation costs due to exogenous or general equilibrium shocks ($\hat{B}$) or an increase in the volume shipped ($\hat{v}$) also rise import prices.[14]

The impact on import demand takes into account local competition and exogenous demand shocks:

$$\hat{q}^M_{ijk} = -\eta^K\hat{p}^M_{ijk} - (\eta^K - 1)\hat{P}^M_{jk} + \hat{Z}^K_{ijk} \tag{9}$$

On top of the price change determinants, an increase in the price index P^M or the demand shifter Z^K also rise local domestic prices.

The above price (8) and quantity equations (9) will guide our empirical strategy at the exporter-importer-product, which we explore in the next section.

3.2 Empirical Strategy

The goal is to estimate equations 8 and 9, the structural price and quantity equations in changes, using the highly-detailed trade and mobility data.

We initially assume that there is no congestion to focus on the direct channels, which in the theory implies assuming that $\alpha^K = 1$. We later provide evidence that it had also a role in shaping trade flows during the pandemic but did not affect the direct impacts. Given that, the three main direct sources of trade disruptions in the model are at the exporter location, importer location and during transportation. In these equations, they are captured by $\hat{A}$, $\hat{Z}$, and $\hat{B}$ respectively. In this section, we focus on the first two terms and leave the impact of

[14]The impact of transport prices on import prices comes from both their accounting relationship and the optimal export price set by the exporter.

$\hat{B}$ for section 5, where we study port disruptions.

3.2.1 Local Demand and Supply Shocks Measurement

We measure local demand and supply shocks using changes in human mobility from Facebook and Baidu, in the case of China. In the model, local disruption shocks during the pandemic can be interpreted as changes in the cost and demand shifters, A^K and Z^K respectively. For instance, a regional lockdown may suddenly reduce labor supply, increasing wages and thus A^K. Moreover, a local pandemic shock may affect the demand for good K products through income and substitution effects, as captured by Z^K.[15]

In order to map these changes to the data, we assume the following empirical relationships.

$$\hat{A}^K_{ik} = \gamma^K_A \hat{x}^I_i + \epsilon_{A,ik} \tag{10}$$

$$\hat{Z}^K_{jk} = \gamma^K_Z \hat{x}^J_j + \epsilon_{Z,ik} \tag{11}$$

where γ^K_A and γ^K_Z are the shifters' elasticities with respect to local mobility, and $\epsilon_{A,ik}$ and $\epsilon_{Z,ik}$ are idiosyncratic mobility changes. We index the elasticities with K to indicate that changes in mobility may have different effects on different goods such as those used directly for consumption.

3.2.2 Empirical Equations

In order to get the empirical equations, we do the following. First, we replace $\hat{A}^K_{ik}$ and $\hat{Z}^K_{jk}$ by expressions 10 and 11 into equations 8 and 9. Second, we do two identification assumptions to deal with (a) changes in transportation costs $\hat{t}$, and (b) the import price index in the quantity equation.

To control for international transport costs, we include an exporting country (c), main port of entry (MPOE, u) and time fixed effect δ^{Tr}_{cut}, where we calculate the main entry port for each exporter, importer, product and time observation.[16][17] Most of the observations in

[15]In appendix section B.2 we provide support to the relationship between the mobility measure and the pandemic shocks.

[16]Note that we call "port" to any entry point of entry to Colombia in this section, including land and airport customs.

[17]We observe transportation costs at this level but we do not include the specific transport variable as a control to avoid including an endogenous variable as a control that is not our main object of interest. In Appendix section B.7.3 we show that the estimated fixed effects are highly correlated with the observed transport costs.

our baseline sample use only a single entry port to Colombia, and in 70% of them the main entry port accounts for the 90% imports.

In the model, the price exporters charge does not depend on j characteristics other than through transport costs. However, quantities demanded at j also depend on the state of competition at that location, captured by the import price index. In order to control for it, we can think of the import price index at location j as having two components. First, the import price index at the entry port, and second, the cost of the internal transportation to location j. Given we do not have data on the latter, we assume that it is absorbed by importer firms and thus is captured by the local importer mobility indicator. To control for the former, we include a product-time fixed effect, δ^P_{kt}.

The resulting empirical equations are as follows:

$$\hat{q}_{ijkt} = \beta^{K,q}_I \hat{x}^I_{it} + \beta^{K,q}_J \hat{x}^J_{jt} + \delta^{P,q}_{kt} + \delta^{Tr,q}_{cut} + \varepsilon^q_{ijkt} \tag{12}$$

$$\hat{p}^M_{ijk} = \beta^{K,p}_I \hat{x}^I_{it} + \beta^{K,p}_J \hat{x}^J_{jt} + \delta^{P,p}_{kt} + \delta^{Tr,p}_{cut} + \varepsilon^p_{ijkt} \tag{13}$$

where the error terms ε^q_{ijkt} and ε^p_{ijkt} result from the approximation error and the idiosyncratic shocks to the demand and cost shifters. Note that we include the import price index fixed effect, $\delta^{P,p}_{kt}$, to both equations for symmetry and comparability, but the model only predicts it to be relevant for the quantity equation.

4 Estimation of the Trade Impact of Disruptions at Exporter and Importer Locations

In this section, we estimate the baseline equations presented in the previous section at the exporter location, importer location, product and month. In doing so, we address multiple identification threats by means of different robustness checks.[18]

4.1 Baseline Results

We start by estimating the empirical quantity (12) and price (13) equations, plus the sum of the two which corresponds to the impact on import values. In columns 1-3 of panel A in

[18] In appendix section B.3, we conduct the analysis at the importer location-month and exporter location-month levels and show that these measures affect import values at that level positively, as expected. Moreover, we show the underlying residual variation used to identify these effects and that they did not have an impact on pre-pandemic imports.

Table 1, we include these estimates with standard errors clustered at the level of the mobility variables—exporter-time and importer-time.

Exporter and importer negative mobility shocks reduced import values as shown in column 1. These effects are explained mainly by a reduction in the imported quantities, as observed in column 2. In column 3 we estimate the impact on import prices and show that only the export mobility shock had a (negative) effect. A decrease in exporter mobility of 10% induced a decrease in import quantities from that location of 3.5% with prices 1% higher, whereas a decrease in importer mobility of the same magnitude lowered import quantities in 4.1%. If we do these calculations at the average importer and exporter reduction in mobility (22% and 13% respectively), we get that the impact on import values was -11% and -3% respectively.[19]

We can recover the elasticity of substitution across locations using these baseline results by taking the ratio of the quantity to price estimates of the export mobility shock, i.e. $-\beta_I^{K,q}/\beta_I^{K,p} = \eta^K$. This yields a $\eta^K = 3.4$, confirming that varieties produced at different locations are imperfect substitutes as assumed. Is this value in line with those found in the literature? In the standard Armington model, where different countries produce different varieties of a good, the elasticity of substitution can be recovered from the trade elasticity—the elasticity of trade flows with respect to trade frictions. The implicit elasticity of substitution using the lower bound in the trade elasticity estimates surveyed in Anderson and Van Wincoop (2003) is 6. Our estimate is in the ballpark considering that standard estimations use annual and country-level variation.[20]

We can also recover the empirical elasticity of the demand shifter with respect to local human mobility using these results. The coefficient of the import mobility in the quantity equation exactly pins down γ_Z^K, suggesting that a decline in importer mobility of 10% induced an average decline in import demand of 4%.

4.2 Pre-trends, Alternative Specifications and Alternative Standard Error Assumptions

Mobility shocks may have affected trade flows differently depending on their flow-specific seasonal patterns and pre-trends. In Table 1, columns 4-6 in panel A, we control for the

[19] Values from Appendix Table A3, where we show the descriptive statistics of the variables used in this section.

[20] We use monthly variation and thus our estimates capture short-run adjustments only. Following Anderson and Yotov (2020), the resulting elasticity should be lower than the standard values. Moreover, we define varieties at the sub-national level. Yilmazkuday (2012) estimates a sub-national goods-specific elasticity of substitutions across US states of 3 on average, similar to ours. All in all, our estimates are in line with these results.

corresponding value during the 2018-2019 period.[21] Results remain similar to the baseline both in terms of magnitudes and significance.[22]

In the two bottom panels of Table 1, we estimate these regressions for alternative fixed effect specifications. In columns 7 to 9, we do not include the product-time fixed effects, which control for industry determinants such as competition in our model. Results do not change substantially. In columns 10 to 12, we exclude the MPOE interaction in the transportation fixed effect, leaving it as a country-time fixed effect. The results hold but are a bit noisier for the exporter mobility. In columns 13 to 15, we assume that the country of origin and MPOE are separable, meaning that we include country-time and MPOE-time fixed effects. Again, results stay the same. Finally, we assume that transportation costs are product-specific and thus we include country-MPOE-product-time fixed effects. Results show the same pattern in terms of significance and sign, but the exporter mobility shock coefficients increase in magnitude in the three cases.

In Table B5, we check if our choice of standard error correction affects results and take a more conservative approach by clustering standard errors at higher levels of aggregation. In columns 1 to 3, we employ exporting country-time and importer location-time clusters, and in columns 4 to 6, we change the latter to importer department-time. Results remain significant.

4.3 Congestion

In our theoretical framework, we allow for production congestion in the short run. In order to test this and confirm our main estimations are robust to this mechanism, we construct and include in the estimations two empirical measures. First, we construct a "supply-side" congestion variable to capture an increase in marginal costs when an exporter cannot expand its capital to satisfy a demand shock. Second, we construct a "demand-side" congestion variable to capture a shock to world demand for a product.[23]

In Table B6, we estimate the baseline and include the demand and supply congestion proxy variables. We stress two main things. First, exporter and importer mobility coefficients do not significantly change from the case without congestion. Second, the demand-side congestion variable is negative, which is consistent with the potential existence of world excess supply. Conditional on the local demand determinants, such excess supply could have been redirected to other locations in the short run.

[21] Specifically, we add $\hat{m}_{ijk,t-24}$, the respective dependent variable, to the right-hand side of the equation (we add $\hat{q}_{ijk,t-24}$ in the quantity equation and $\hat{p}_{ijk,t-24}$ in the price equation).

[22] Estimates without pre-trend controls with the same sample of observations yield indistinguishable results from the baseline in terms of sign, magnitude and significance.

[23] Please see Appendix section A.6 for details in how we construct these variables.

4.4 Heterogeneity by Type of Good

In this section, we estimate equations 12 and 13 allowing for goods heterogeneity depending on the type of use. We employ the Broad Economic Categories (BEC) classification to identify products falling into the consumer, intermediate and capital goods categories, and estimate the baseline specification allowing for different elasticities depending on the type. We present results in Table 2, panel A.

Importer mobility shocks affected the three types of goods similarly. Based on our framework, the only reason why these coefficients may vary is through differences in γ_Z^{cons}, the empirical relationship between mobility and the demand shifter. These estimates suggest a non-goods-specific relationship between these two objects. Importantly, the theoretical prediction of not having an impact on import prices holds for all of them. Again, this suggests that Colombian demand is small in average from the suppliers' perspective.

We observe differences in the impact of exporter mobility across types of goods. Their impact on intermediate goods is very similar to the baseline specification:[24] a negative shock decreased quantities and increased prices. This is not the case in the case of consumer goods, where we only observe an impact through import prices. The only difference in the export mobility coefficient between the quantity and price equations is the elasticity of substitution across varieties. Potential heterogeneity in this parameter across consumer goods may be attenuating this coefficient down. Finally, exporter mobility only affected capital goods imports through quantities and not prices, potentially reflecting a higher degree of price stickiness in this type of good.

We also explore if mobility shocks affected the demand and supply of medical products differently given the nature of the shock.[25] If they capture local pandemic shocks, a negative change in this variable should be associated with an increased demand and a reduced supply of medical products. This is what we find in panel B of Table 2.

4.5 Other Heterogeneous Impacts

We explore other potential heterogeneous effects by employing data from other studies. In all cases, we employ product-specific measures and the interaction term captures whether there is a differential effect for higher values of the respective measure.[26]

[24] Intermediate goods account for about 60% of the sample.

[25] We identified Covid-related medical goods based on a list of products put together by the World Customs Organization and World Health Organization. See Appendix section B.5 for details.

[26] We employ measures of upstreamness from Antras et al. (2012), price stickiness from Nakamura and Steinsson (2008), inventory intensity from Fajgelbaum et al. (2020), and differentiated goods indicator from Rauch (1999).

In columns 1 and 2 of Table 3 we present the impact based on upstreamness. Industries at relatively more upstream stages of production experienced a stronger impact on imported quantities, consistent with the fact that more basic stages of production may require labor intensively. In columns 3 and 4, we explore price stickiness and, as expected, the import price elasticity with respect to export mobility shocks is lower for sectors with more sticky prices. Note also that the quantity elasticity to import mobility shocks is higher in magnitude for these sectors. Even though we do not find an impact on import prices for importer shocks, if they were to adjust less, this would be the expected result.

In columns 5 and 6, we explore the inventory intensity measured by inventory-to-sales ratios in the US. We would expect a stronger impact of importer mobility on those sectors with typically higher values, as they can use their inventories instead of importing. This is what we observe. Finally, in columns 7 and 8 we explore whether there is a heterogeneous effect on differentiated products. In this case, negative importer mobility shocks reduced importer quantities by more. In presence of an income effect, this may be expected, as consumers may relatively increase demand for more homogeneous goods. Note also that its impact on import prices is lower and even closer to zero, which is what we would expect if prices are determined by monopolistically competitive exporting firms.

Finally, we explore if local disruption shocks at the importer location may correlate to regional shocks. In appendix section B.6, we show that the impact is stronger the more narrowly we measure the mobility impact. For instance, the correlation is higher for the five closet municipalities than for the department average.

4.6 Interaction Between Importer and Exporter Mobility

Exporter and importer mobility shocks may have had a stronger impact if both happened at the same time for a given product. Specifically, some trade activities could have been taken over by either the exporter or the importer if only one shock happened. In Appendix Table B7, we replicate the baseline table with goods heterogeneity and include an interaction term between the exporter and importer mobility shock variables.

Let's first focus on intermediate goods. The interaction between both mobility shocks is significant and has the opposite sign as the individual estimates. This means that the marginal effect on quantities and prices of both shocks increased in magnitude when there was a shock on the other extreme of the supply chain. Note that this is the case at the mean exporter and importer mobility shocks.

In the case of consumption goods, the marginal effect of exporter mobility shocks on consumption is close to zero at the mean as expected based on the baseline results. However, the negative interaction term implies that the marginal effect was negative at low values of import mobility shocks. Their impact on import prices became higher in magnitude for stronger import mobility shocks.

4.7 Extensive Margin

In this section, we explore the impact of exporter and importer mobility changes on the extensive margin, defined at the exporter-importer-product level, by means of a linear probability model in differences. Specifically, we estimate the following equation:

$$\hat{I}_{ijkt} \quad = \quad \beta^J \hat{x}^J_{jt} + \beta^I \hat{x}^I_{it} + \delta^{P,E}_{kt} + \delta^{Tr,E}_{ct} + + \varepsilon_{ijkt}, \tag{14}$$

where $\hat{I}_{ijkt} = I_{ijk,t} - I_{ijk,Feb20}$ is the difference of an indicator that takes the value of one if we observe a flow at the exporter-importer-product-time level. As with the baseline, we take the difference against February 2020, and thus the dependent variable can take three values, -1, 0, and 1.

In Table B8 column 1, we show the results for the baseline estimations. Both exporter and importer mobility changes positively affect the extensive margin — i.e., both exporter and importer declines in mobility reduced the export participation in Colombian import markets at the product level. In column 2 we control for congestion variables and find no differences in the mobility coefficients. A negative demand shock as captured by a decrease in the demand-side congestion variable increased the presence of trade flows, probably due to reallocation. An exporter shock had the opposite effect, as exporters may have experienced limitations to serve the increased demand in the presence of shocks to competitors. Finally, we included the interaction between exporter and importer mobility shocks in column 3, but in this case, it was insignificant.

4.8 Discussion

In this section, we presented a battery of results that point towards a robust effect of local trade disruptions on international trade flows, both for quantities and prices. Specifically, export mobility shocks increased import prices and decreased import quantities, and import mobility shocks declined import quantities, consistent with our theoretical framework. This is especially the case for intermediate goods, which are relatively more isolated from consumer substitution and income effects in the short run.

In the next section, we explore the impact of trade disruptions when they occur at port locations. The goal is to both document the importance of such shocks at intermediate points of the supply chain, and to pin down their effect on transport prices so we can analyse their relative importance.

5 Trade Disruptions at the Sea Ports

In this Section, we investigate the impact of trade disruptions on the price of transportation. Trade disruptions include direct labor mobility changes and cumulative effects of the pandemic-induced congestion in the transportation network. We focus on the exporter country and discuss briefly the role of intermediate countries.

5.1 Econometric specification

First, we investigate the relationship between the mobility change and port performance in the exporter country using the following equation:

$$\hat{Y}_{cym} = \alpha_0 \hat{x}^{\text{Ports}}_{cym} + \delta_m + \delta_y + \delta_c + \epsilon_{cym}, \tag{15}$$

where $\hat{Y}_{cym}$ can be the change in log number of hours each container ship spends in ports or the change in log the number of port calls made by container ships in exporter country c, year t, and calendar month m. We control for calendar month fixed effects (δ_m) to take into account seasonality, year fixed effects (δ_y) to allow for different levels in 2020 and 2021, and exporter country fixed effects (δ_c) to allow different countries to have different overall changes.

For exporter country c, we measure the average change in mobility in ports as the average mobility change in cities where the ports are located in:

$$\hat{x}^{\text{Ports}}_{cym} = \sum_{p(c)} \frac{\text{TEU}_{p(c)2020}}{\sum_{p'(i)} \text{TEU}_{p'(c)2020}} \hat{x}_{p(c)ym}, \tag{16}$$

where $\hat{x}_{p(c)ym}$ is the change in log mobility in the city where port p in country c is located in, year y, and month c, compared to February 2020, and $\text{TEU}_{p(c)2020}$ is the average monthly twenty-foot-equivalent units (hereafter, TEU) in port p in February 2020. This is calculated using all the container ships that arrived at port p in 2019, and the twenty-foot-equivalent unit is a measure of the ship capacity. Intuitively, higher weights are assigned to ports that process ships with larger capacities. We aggregate across ports within a country since in the Colombian trade data, we don't observe the exact city where the exports are shipped.

Similarly, we compute the average change in the number of port calls made by container ships and the number of hours each ship spend in port (i.e., $\hat{Y}_{cym}$) using the same TEU weights and replacing $\hat{x}_{p(i)ym}$ with the $\Delta \log(\text{Call}_{p(i)ym})$ and $\Delta \log(\text{Hour}_{p(i)ym})$, respectively. Again, the differences are taken with respect to the corresponding values in February 2020.

The parameter of interest α_0 captures the impact of port mobility changes on port performances in the exporter country. More productive ports are able to process a larger number of port calls in a shorter period of time. Our hypothesis is that labor shortage in port cities will lead to a reduction in port productivity. We expect a negative α_0 when the outcome variable is the change in the log number of hours in port, and it indicates that less mobility in port cities leads to longer hours in port for each ship. The effect on the change in the log number of port calls should be opposite, since labor shortage at port cities will lead to fewer port calls being processed.

The first identification assumption is that conditional on the fixed effects, there are no other variables that are driving both the changes in mobility and the changes in port performance.

Second, in terms of reverse causality, the assumption is that changes in port productivity do not lead to changes in human mobility locally. For example, if the ports that receive more port calls made by container ships lead to more infections of Covid-19, the assumption is violated. We think that this situation is not very likely, since the spread of the virus is more likely through passenger traffic rather than cargo traffic, and the bulk of the passenger traffic is via air and via land, instead of via sea.

Third, we need the mobility change to measure the labor supply shock in ports accurately. People may be sick or self-isolating due to the Covid-19 situation, the government may issue stay-at-home orders or other measures to encourage social distancing, and people can choose to stay at home to avoid human contact. The mobility change will capture all three scenarios. In terms of port productivity, we assume that people who work in the ports are subject to the same shocks as people who work in the same city but in other industries.

Our second set of analysis is to investigate the impact of the port mobility declines on freight costs using product-country level data. We keep the trade flows with sea as the method of transportation and also drop "fuel and lubricants" since they are not likely to be transported by containerized ships.[27]

The cost of shipping can be measured in two ways: the freight cost per unit and the freight cost per weight. We calculate the change in log freight cost using the February 2020 value as the baseline. The regression is as follows:

$$\hat{T}_{kcym} = \beta_0 \hat{x}^{\text{Ports}}_{cym} + \delta_m + \delta_y + \delta_c + \delta_k + \epsilon_{kcym}, \tag{17}$$

[27]We use the mapping between HS codes and Broad Economic Categories (BEC) codes as in Staff and Division (2003) and drop goods that have a BEC code of 31, 32, and 322.

where $\hat{T}_{kcym}$ is the change in freight cost in product k, exported by country c, and in year y, and calendar month m. We control for month fixed effects to take into account seasonality, year fixed effects to allow for different levels in 2020 and 2021, product fixed effects, and origin country fixed effects.

The parameter β_0 being negative indicates that a decline in port mobility increases the cost of shipment through the port. The identification assumptions of β_0 are similar to the ones discussed earlier. In sum, we need the local labor supply shocks to be good measures of port labor supply shocks, and the freight costs should not determine in turn the disease transmission and corresponding mobility changes.

In our analysis, we will also use the pre-Covid period as a placebo test. Specifically, we use the outcome variables where the changes are calculated using the months starting from March 2018 until October 2019, compared to February 2020, instead of using March 2020 to October 2021.

5.2 Variation in the port performance and freight costs

This Section presents the variation in the outcome variables of interest. Figure A2 Panel (a) shows the distribution of country-level changes in the log number of hours each ship spend in port in the post-Covid period (March 2020 to October 2021). The distribution is spread out, ranging from -0.4 to 0.6, and more observations are having a positive change than negative changes. This is consistent with the aggregate trend in Figure 3 Panel (c). In addition, as shown in Figure A2 Panel (c), the positive changes are concentrated in 2021.

Panels (b) and (d) present the distribution of changes in the log number of port calls in the post-Covid period. Note that the baseline period is February 2020. As noted in Figure 3 Panel (a), the aggregate number of port calls is the lowest in February in all three years (2019, 2020, and 2021). This is likely to be driven by the fact that the Chinese New Year is usually in late January and late February, and the number of port calls made in Chinese ports is small in this period.[28] Panel (b) shows that the distribution is spread out, ranging from -0.4 to 0.65, and Panel (c) shows that the 2021 distribution is to the left of the 2020 distribution. This is consistent with the overall trend in Figure 3 Panel (a), where we observe a decline in the number of port calls since June 2021.

Figure A3 presents the variation in the changes in freight costs. Panels (a) and (c) show the distribution of the change in log freight cost per unit, and (b) and (d) for the change in log freight cost per weight. The top and bottom one percent of the observations are dropped for

[28] An alternative way of measuring the changes is to use the monthly average in 2019 as the baseline. Our regression results are robust to using this alternative measure.

both variables.[29] In both cases, there are more observations with positive changes, indicating an increase in the freight cost. In addition, the positive changes are more prominent in 2021 than in 2020.

5.3 Regression Results

Table 4 presents the regression results for the country-level regression on port performance. Panel A presents the main results where the port performance measures are changes in the post-Covid period (March 2020 to October 2021), and Panel B presents placebo results where the port performance measures are changed in the pre-Covid period (March 2018 to October 2019). In both cases, the baselines are February 2020.

In Panel A Column (1), the change in the log number of hours each ship spends in port is regressed on the change in human mobility, and we control for year fixed effects, month fixed effects, and origin country fixed effects. The coefficient estimate for the change in log mobility is -0.129, indicating that a one-percentage-point larger decline in mobility resulted in a 0.13-percentage-point increase in the number of hours in port. Evaluated at the mean change in mobility (-0.16), there is a 2.1 percent increase in the number of hours in port. This result suggests that labor shortage lowers port productivity and generates delays.

Importantly, the fixed effect for the year 2021 has a positive coefficient of 0.169, indicating that the average number of hours in port in 2021 is 17% higher in 2021 compared to 2020. Given that the overall mobility improved from 2020 to 2021, this positive coefficient may reflect the accumulated effects of supply chain disruptions. For example, suppose that the pandemic shifts the global trade pattern and that some regions become more important exporters. Then ports need to adjust to the changes in the ship movements under the new trade pattern. These changes can induce delays in processing time at the port. In addition, the pandemic has interrupted other transportation sectors, such as the trucking industry. If it is hard to load the goods from container ships to trucks and ship them domestically, ships have to stay longer at the port as well. Such disruptions have been discussed in the case of the Los Angeles Port, but the situation can be quite general.[30]

Column (2) uses an alternative measure to capture the accumulated pandemic effect, by controlling for a time trend instead of the year fixed effect. The coefficient estimate for the change in log mobility stays the same, and we see an average of 1.4% increase in the number of hours in port for each additional month.

Column (3) has the same specification as Column (1) and uses the change in the log

[29] Our regression results are robust to keeping all observations.

[30] See news reports: `www.wsj.com/articles/truckers-steer-clear-of-24-hour-operations-at-southern-california-ports-11637173872`.

number of port calls made by container ships as the measure for port performance. We find that increased mobility also allows more calls to be processed. Evaluated at the mean change in mobility (-0.16), it induces a 1.7 percentage decrease in the number of hours in port. Column (4) controls for the time trend and finds similar results.

Columns (5) and (6) confirm that in ports where more calls are processed, each call also takes a shorter time. In this sense, both shorter time in port and more calls are indications of a good performance in the port, similar to the quality and quantity aspects of a good produced by a firm.

In Panel B, we use the pre-Covid changes instead of the post-Covid changes. The coefficient estimates for the change in log mobility are small and statistically insignificant, indicating that the mobility changes in the post-Covid period are not associated with the port performances in the pre-Covid period. In addition, there is not a statistically significant association between the two measures of port performance. This suggests that in the pre-Covid period, the ports seem to be not constrained in their capacities.

Figure B14 shows the residual plots for results in Table 4 Panel A Columns (1) and (3) and Panel B Columns (1) and (3). We also conduct robustness checks by dropping one country at a time and by dropping one period at a time. The corresponding results are shown in Appendix Figures B16, B17, and B18. Overall, we find that the results are not driven by one particular country or period.

Overall, we find that mobility reductions at the ports indeed have a negative impact on port performance and that the pandemic has an accumulated effect on port delays.

Then we proceed to investigate the impact of mobility changes on freight costs. Table 5 shows the regression results. Panel A presents the main results with post-Covid price changes, and Panel B presents placebo results using the pre-Covid period price changes. In both cases, the baselines are February 2020.

Panel A Columns (1)–(4) use the change in log freight cost per unit as the outcome variable. Column (1) controls for year fixed effects, calendar month fixed effects, product fixed effects, and exporter country fixed effects. The coefficient estimate for the change in log mobility in the exporter country is negative and statistically significant at the 5% level. This indicates that a one percent decrease in mobility results in a 0.25% increase in the freight cost. Evaluated at the mean change in log exporter mobility (-0.14), there is a 3.8-percentage-point increase in the freight cost. Results are similar when Columns (2) uses the time trend instead of year fixed effects, Columns (3)–(4) control for different sets of fixed effects. Columns (5)–(8) find similar results by using freight cost per weight as the outcome variable.

Again, the fixed effect for year 2021 has a large and significant coefficient, indicating that the 2021 level is 51% higher than the 2020 level (Column 1). Similarly, the monthly increase in freight cost is 4% (Column 2). This pricing effect can come from the increased demand in 2021 or the accumulated supply chain disruptions.

We don't find statistically significant effects when we run placebo regression using pre-Covid changes in Panel B.

Unlike the port performance regressions, it is harder to visualize the coefficients for the product-level freight costs using a residual plot. Thus, we take the mean of price changes at the country-period level and run similar regression as in Table 5. The residual plots are shown in Figure B15. Reassuringly, the country-level regression results are similar to the product-level results.

Overall, we find that mobility declines in port had significant impacts on the price of the transportation sector.

5.4 Intermediate Ports

The cost of shipping not only depends on the exporter country ports but also the intermediate shipping ports. As shown in Ganapati et al. (2021) and Heiland et al. (2019), the majority of trade is indirect, making at least one stop along the way. We compute the average change in mobility, the number of port calls, and the number of hours in port for potential intermediate countries. We use the optimal country-to-country shipping routes computed in Ganapati et al. (2021) to measure the intermediate country shocks since we don't observe the actual shipping routes in the Colombian trade data. For each of the 25 major trading partners with Colombia, we consider two intermediate stops. For the first intermediate country K, the average mobility change is

$$\Delta \log(\text{mobility}_{iym}^{K}) = \sum_{k} \frac{\text{prob}(k(i))}{\sum_{k'} \text{prob}(k'(i))} \Delta \log(\text{mobility}_{k(i)ym}^{\text{Ports}}), \tag{18}$$

where $\Delta \log(\text{mobility}_{k(ir)ym})$ is the change in mobility in country k, year y, and month m, compared to the pre-Covid period, and $\text{prob}(k(i))$ is the probability that the optimal route from country i to Colombia uses country k as the first intermediate stop. We compute the second intermediate country's mobility change similarly ($\Delta \log(\text{mobility}_{iym}^{L})$), by using the probability of being the second stop. We also use similar weights to calculate the number of port calls and the number of hours in port in the first intermediate country and the second intermediate country.

Note that we use the country-level port averages since the Colombian trade data does not report the exporting and intermediate ports, but only the countries. By taking the averages, we are essentially assuming that in a country, a large port for all container trade is also a large port for trade with Colombia.

Similarly, we can run the regressions for port performance measures and freight costs using measures for the first intermediate country mobility and the second intermediate country mobility. Table 6 shows the results for the impact of mobility changes in the exporter country and in intermediate countries on the freight costs. Column (1) replicates Table 5 Panel A Column (1), Columns (2) and (3) use changes in mobility in the first and the second intermediate country, respectively Interesting, the effects are even larger for mobility declines in the intermediate ports. One interpretation is that the intermediate ports are likely to be the entrepôt as discussed in Ganapati et al. (2021), and the reduction in mobility in those transportation hubs is more costly than in individual export countries.

6 Impact Decomposition of the Disruptions at Exporter, Importer and Transport Locations

In previous sections, we documented the impact of mobility changes at the exporter, importer, and port locations on the quantity and prices of imports by Colombia. In this section, we bring together the evidence and do a decomposition of the relative effects coming from different sources. In particular, we are interested in the decomposition over time (in the 20 months we study).

6.1 Method

Recall that in Equation 12 and 13, the change in log quantity and import price can be written as a function of the change in log exporter mobility $\hat{x}_{it}$, the change in log importer mobility $\hat{x}_j t$, and a set of fixed effects. Specifically, we can compute the total predicted changes in quantity and prices as

$$q^T \equiv \hat{\beta}_I^{k,q} x_I^T + \hat{\beta}_J^{k,q} x_J^T, \tag{19}$$

$$p^T \equiv \hat{\beta}_I^{k,p} x_I^T + \hat{\beta}_J^{k,p} x_J^T, \tag{20}$$

where we condition on the fixed effects. Note that the fixed effects will incorporate general equilibrium effects that are endogenous. For example, $\delta^{Tr,p}$ will capture the change in exporter-country-importer-port-specific transportation costs.

Thus, for maritime trade, we can further decompose the $\delta^{Tr,q}$, where transportation costs are shown to be affected by change in mobility in ports in exporting countries. Thus, we can write the predicted changes in shipping costs as

$$t^T \equiv \hat{\beta}_0 x^T_{Port} + \hat{\beta}^{trend}\text{time}. \tag{21}$$

As shown in Equation 7, we can write the $\delta^{Tr,p}$ and $\delta^{Tr,q}$ as follows:

$$\hat{\delta}^{Tr,p} = (1-\bar{\iota})t^T + \epsilon^{Tr,p}, \tag{22}$$

$$\hat{\delta}^{Tr,p} = -\hat{\eta}(1-\bar{\iota})t^T + \epsilon^{Tr,q}. \tag{23}$$

The average share of transportation cost in import price $\bar{\iota}$ in 2018 and 2019 is 7%. Then we use the coefficient estimates from the previous sections to conduct the decomposition.

6.2 Time series

By using the average mobility changes in each time period, we can do the decomposition of the total effects over the 20 months we study. We focus on intermediate products given that the predicted shock at both exporter and importer locations can be more directly interpreted following the theory and the empirical results.[31] Results are shown in Figure 7.

We find that for quantity, importer mobility shocks explained 67%, exporter shocks 26% and port shocks 7% at the onset of the pandemic (April 2020). The transportation sector increased its importance over time. In terms of import prices, the direct price effect in April 2020 was explained entirely by exporter mobility shocks, but the importance of the transportation sector increased over time as well given its positive linear trend.

6.3 By product

We also want to see which products suffered the most. The size of the impact will depend on (1) how many suppliers; (2) the average mobility change in each supplier; (3) the correlation of the mobility change across different suppliers.

Did products with larger numbers of supplier countries or larger numbers of supplier cities experience differential shocks? We find similar mean and standard deviation for exporter mobility changes.

7 Is Inflation Related to Trade Disruptions?

In this section, we study the relationship between trade disruptions and consumer prices in Colombia. Specifically, we analyse if consumer goods for which its imported products were

[31]Results for consumption products are in the Appendix section B.9.

sourced from cities that experienced higher negative mobility shock had higher price hikes. To do so, we leverage monthly goods-specific national indices that form the building blocks of the Colombian Consumer Price Index (CPI).[32]

7.1 Consumer Price Index

The aggregate Colombian CPI is constructed by aggregating indices defined at five-digit goods categories based on the COICOP classification.[33] This classification has 188 categories called "sub-classes" covering both goods and services. We are interested in the direct relationship between CPI's sub-classes and imports, and thus we matched the consumer products for which we observe positive imports per month to these sub-classes.[34] On average, we find that an average of 56 sub-classes have a direct correspondence to imports.[35]

In Figure 8, we plot the month-specific distribution of the goods sub-classes with direct correspondence to import products along with the aggregate CPI computed by using the sub-class specific national expenditure weights. Consumer prices did not increase substantially in 2020 but started increasing in 2021. In October 2021, the median consumer price index was 7% higher than in February 2020, and the aggregate consumer price was 5% higher.

7.2 Import Price Index Computation

In order to study the relationship between consumer price hikes and mobility shocks, we need to compute comparable import price changes due to changes in mobility. To do so, we first computed the predicted change in import prices of consumer goods using the specification that distinguishes between types of goods. The outputs of that exercise are the predicted import price changes relative to February 2020 at the $ijkt$ level, i.e. exporter location, importer location, product and month level.

Secondly, we aggregated each $ijkt$ observation in the trade data to the CPI goods sub-classes (κ). We conducted a concordance exercise that yielded a direct mapping between each consumer product a six-digit HS code k and a five-digit code κ based on COICOP.[36]

[32] We do not have access to city-goods specific indices for now.

[33] The Classification of Individual Consumption According to Purpose (COICOP) is a classification of goods and services designed by the UN to analyse the consumption pattern of households and non-profit institutions.

[34] We abstract from the indirect impact through intermediates products.

[35] This figure is fairly constant over time, varying from 52 to 59 sub-classes in the sample period (March 2020 to October 2021).

[36] We employed the available UN concordances between the two and manually concorded the ones that did not have a direct correspondence. We only used the HS codes identified as consumer products by the BEC classification. The average (median) number of six-digit HS codes within a five-digit CPI code is 8 (4).

Finally, we computed pre-pandemic ijk weights specific to each κt to calculate the κ-month specific import price change:

$$\hat{p}^M_{\kappa,t} = \sum_{ijk\in\Omega_{\kappa,t}} \theta_{ijk,t}\hat{p}^M_{ijkt} \tag{24}$$

where $\theta_{ijk,t} \equiv \frac{m^{2019}_{ijk}}{\sum_{ijk\in\Omega_{\kappa,t}} m^{2019}_{ijk}}$.

In Figure A10, we plot the month-specific distribution of the 24 observed import price changes, converted to import price indices with base in February 2020. The time series pattern is the same as in the case of the consumer price indices, but the magnitude of the changes is larger. In October 2020, the median import price index was 11% higher than in February 2020.[37]

7.3 Relationship between Consumer Price Index Changes and Mobility Shocks

To study the relationship between consumer prices and mobility shocks, we first compute $\hat{p}^{M,m^X}_{\kappa,t} = \hat{\beta}^I\hat{x}^I_{it}$, i.e. the import price change predicted by mobility shocks at the exporter location. Then, we fit the following equation:

$$\hat{p}^C_{\kappa,t} = \mu\hat{p}^{M,m^X}_{\kappa,t} + \delta^T_t + \zeta_{\kappa,t} \tag{25}$$

where $\hat{p}^C_{\kappa,t}$ are log consumer price changes as converted from consumer price indices, μ captures the pass-through from export mobility shocks on Colombian consumer prices, and δ^T_t is a month fixed effect to focus on the product variation.

In Table 7 column 3, we estimated this equation. The estimated pass-through is $\hat{\mu} = 0.575$, meaning that an increase of 10% in import price due to export mobility shocks was related to a consumer price increase close to 6%. In Figure B20 we plot the relationship between the residualised consumer price changes and the predicted import prices.

How does such pass-through relate to the overall observed pass-through? In columns 1 and 2, we employed the observed import price changes and the predicted import prices using the full model. The resulting pass-throughs are 0.013 and 0.011 respectively, more than an order of magnitude lower. This means that by isolating the effect from export mobility shocks we can see that the pandemic directly affected consumer prices. This result is robust to including shocks to the transportation sector, as captured by transport price changes, as

[37] We do not take a stance on the aggregate import price as we do not have expenditure weights specific to import goods.

shown in column 5.[38]

In conclusion, this evidence suggests that part of the increase in inflation observed during the pandemic was related to negative production shocks at exporters that propagated through the international supply chain.

8 Conclusion

We studied the impact of local disruptive shocks on international trade during the pandemic. Using Colombian' customs data, we first documented the sudden decrease in import quantities and the steady increase in export prices and shipping costs. We then documented port congestion by showing that the average hours in world port increased throughout the pandemic.

We found that local mobility shocks at the exporter and importer locations reduced product import values and trade participation. We then documented that country-level average port congestion and mobility shocks at ports increased freight unit values.

We then employed a trade framework to decompose the impact into an exporter, importer, and transportation shock. We found that most of the impact at the onset of the pandemic was due to negative demand shocks. The transportation sector increased its importance in the total decrease in import quantities and rise in import prices over time.

Finally, we showed that local disruptive shocks at exporters that increased import prices were related to increases in consumer prices of products sourced from those locations.

[38]We projected the country-port-time fixed effect on observed transport prices and used the predicted effects to construct the transport price shocks. Their individual impact on consumer prices is positive but noisy, as shown in column 4.

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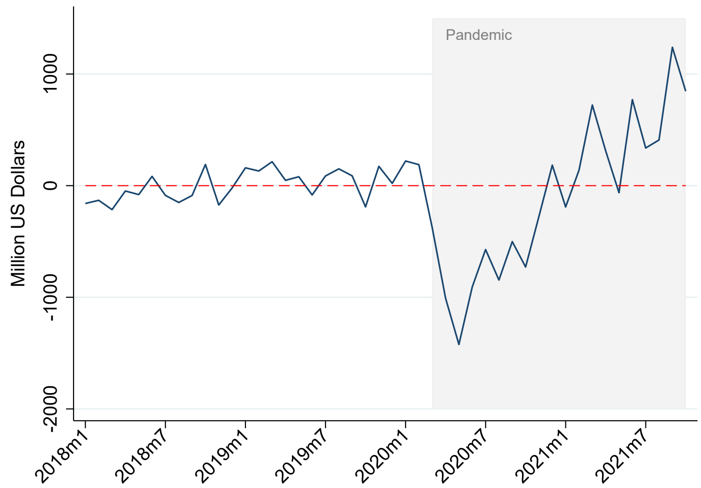
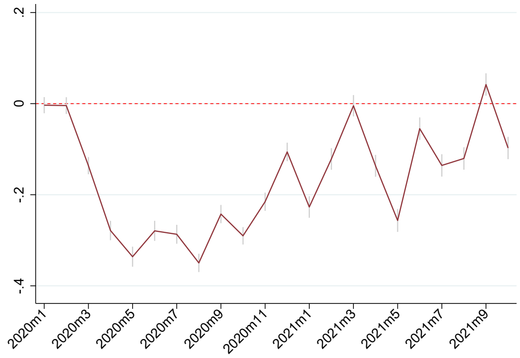
Figures and Tables

Figure 1: Aggregate Colombian Imports Relative to Pre-Pandemic Levels

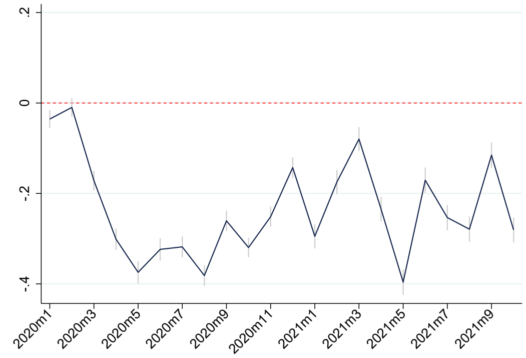


Note: Data from DIAN (the Colombian Office of Taxes and National Customs) made available by DANE (the National Administrative Statistical Office). Each month's value is calculated as the total Colombian imports minus the 2018–2019 month-specific average. Twenty-eight selected countries (90% of total Colombian imports in 2018).

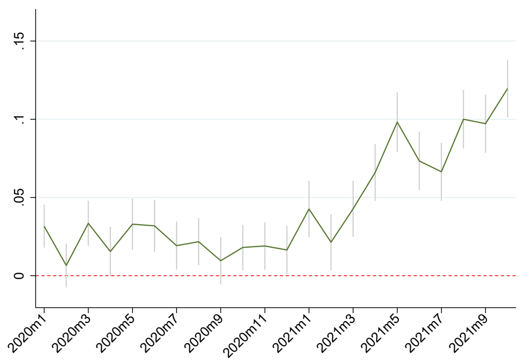
Figure 2: Average Change in Trade Outcomes Relative to Pre-Pandemic Trends



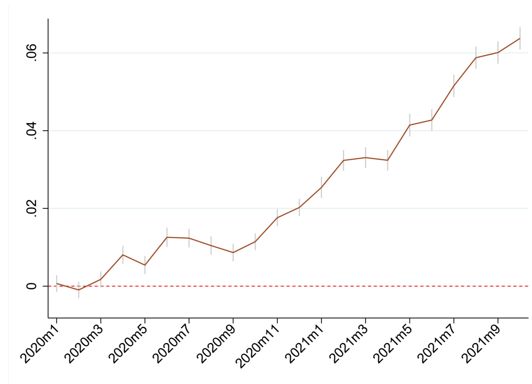
(a) Import Values (m)



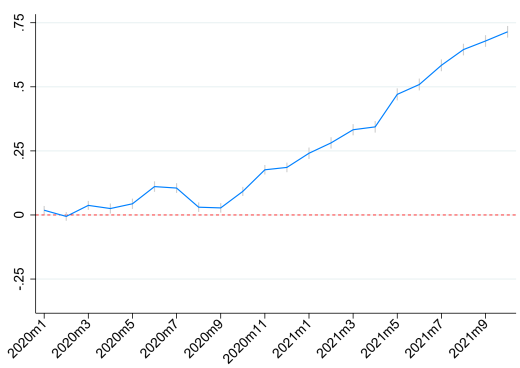
(b) Import Quantities (q)



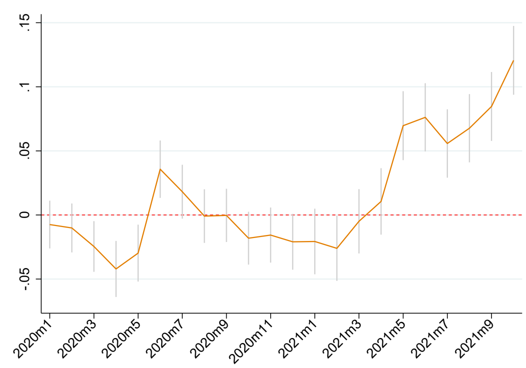
(c) Export Prices (p^X)



(d) Ad-valorem Transportation Costs (τ)



(e) Freight Unit Costs (p^F)



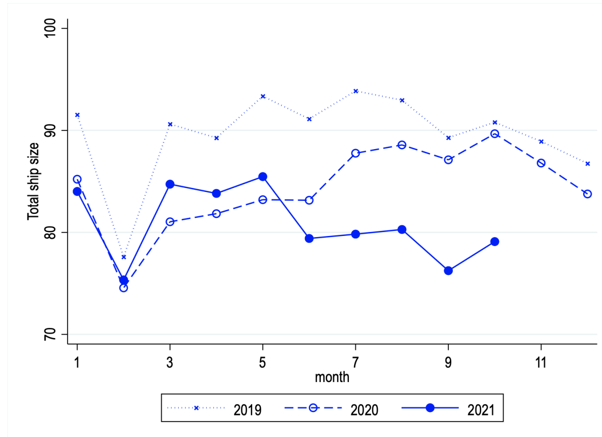
(f) Insurance Unit Costs (p^I)

Note: Data from DIAN (the Colombian Office of Taxes and National Customs) made available by DANE (the National Administrative Statistical Office). Each point is the estimated coefficient of Equation 2 with 95% confidence intervals. Standard errors clustered at the exporter-importer-product level.

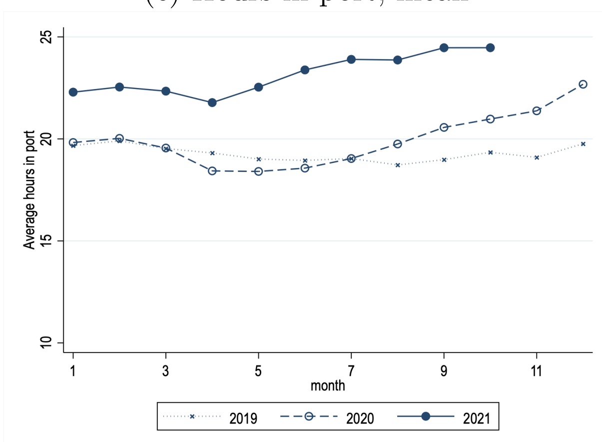
Figure 3: Port performance from January 2019 to October 2021, 150 ports in 27 countries

(a) Total number of port calls in 1000

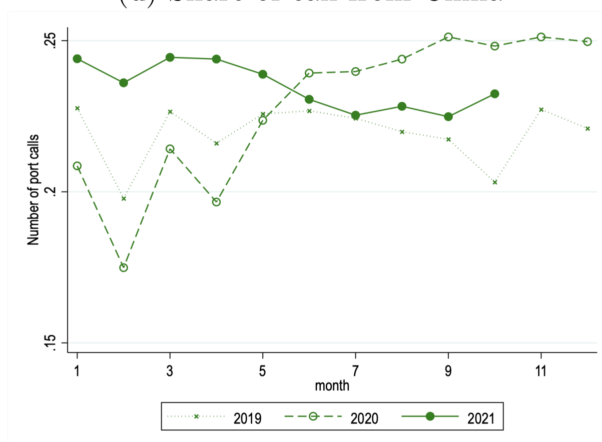
(b) Total ship size in million



(c) Hours in port, mean

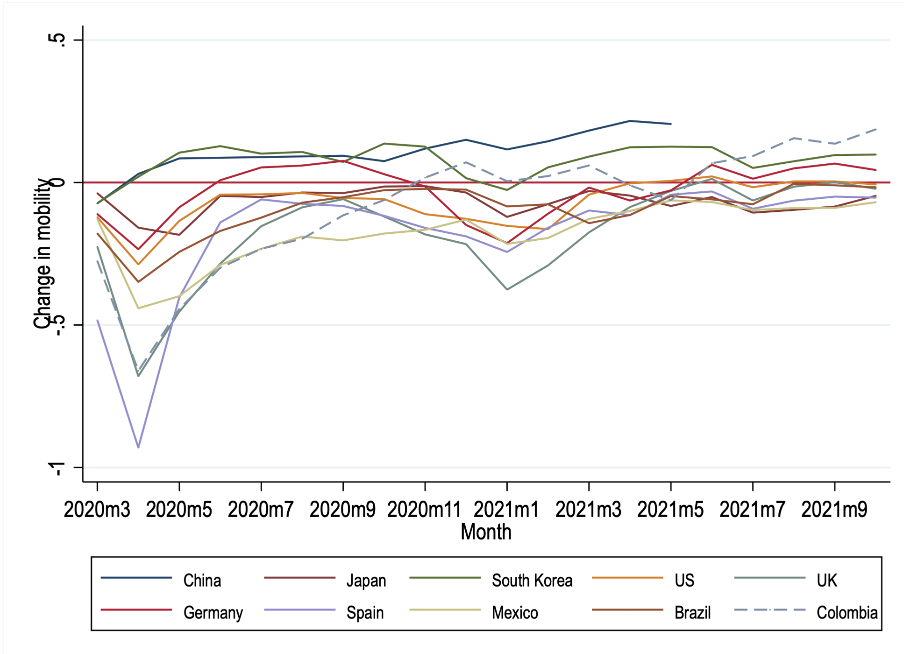


(d) Share of call from China



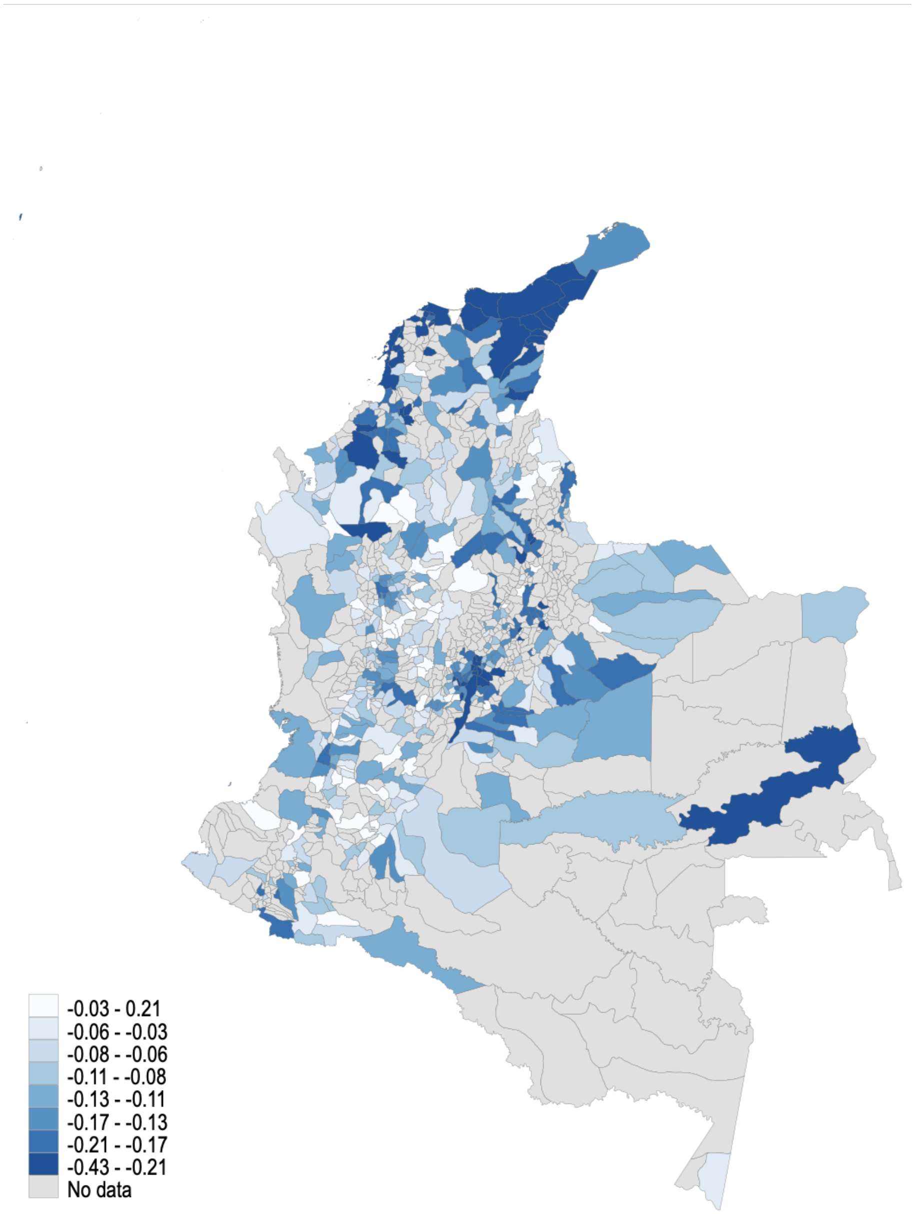
Note: Data is from the IHS Markit Maritime & Trade Platform. The figures use port calls made by container ships at 150 ports in 27 countries. The total number of port calls is in 1000 units, and the total ship size is in millions of twenty-foot equivalent units. The hours in port are measured as the difference between the sailed time and the arrival time at the port. The share of calls from China is measured as the share of port calls whose last port of call was in a Chinese port.

Figure 4: The Trend of Mobility in Exporting Cities Across Countries and in Colombia



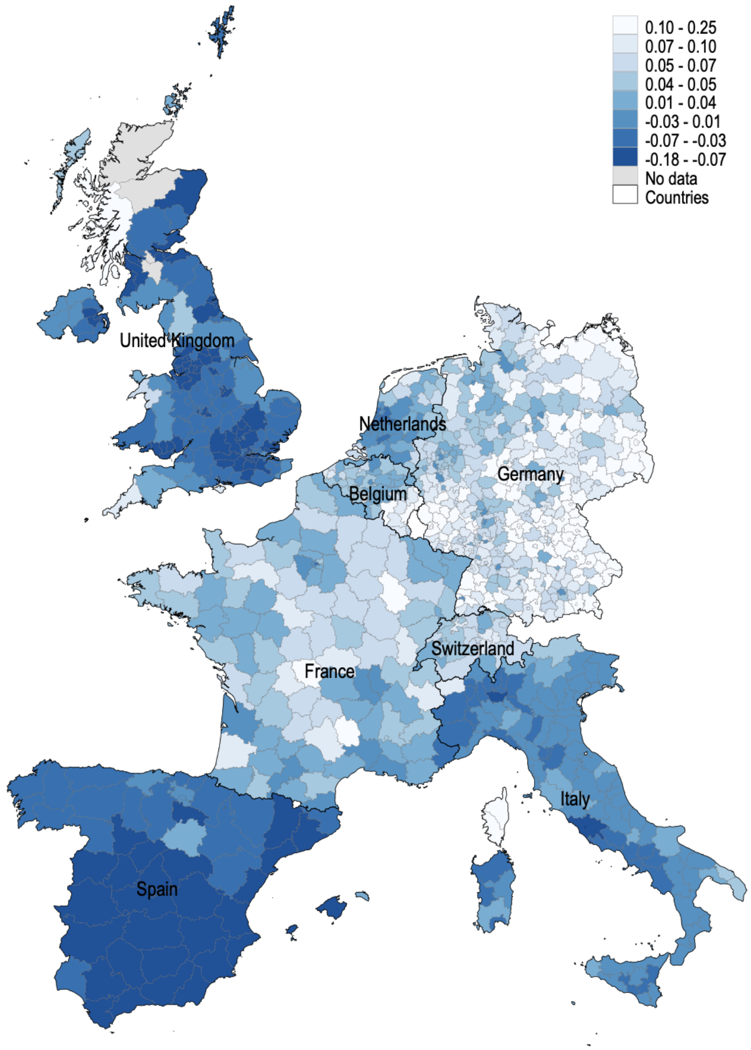
Note: Include only cities that export to Colombia and have mobility data. Data on Chinese mobility is from Baidu, and for other countries, comes from Facebook.

Figure 5: The Decline in Mobility Across *Municipios* in Colombia, September 2020



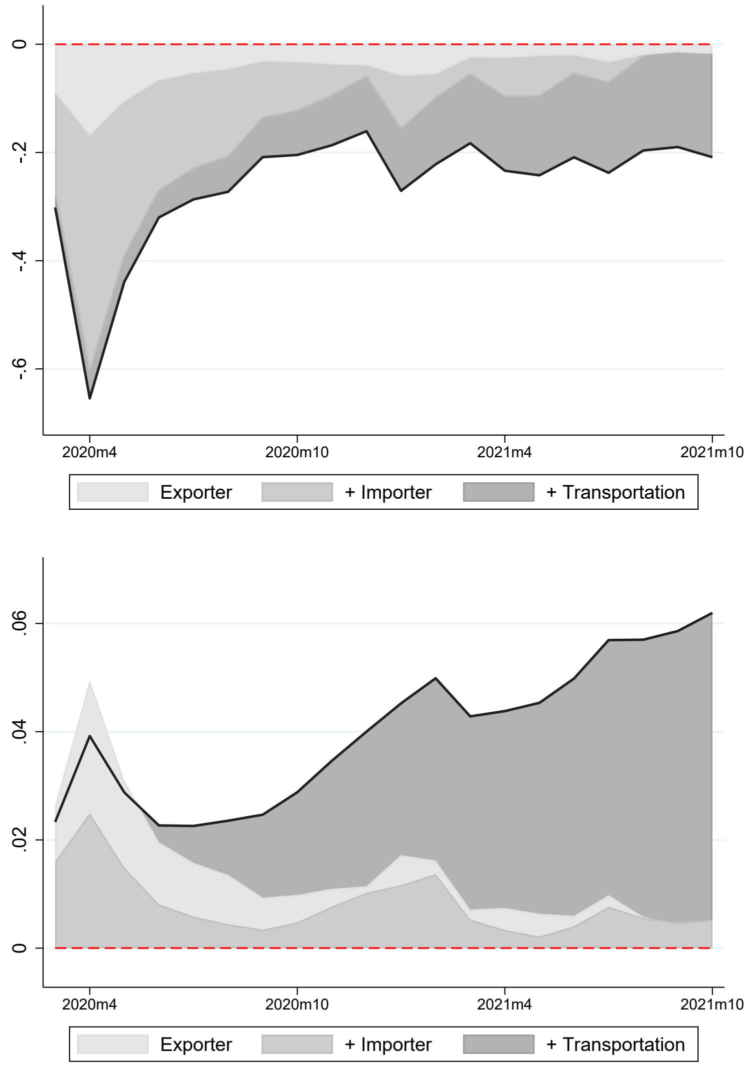
Note: Data is from Facebook.

Figure 6: The Decline in Mobility Across NUTS3 Units in 8 European Countries, September 2020



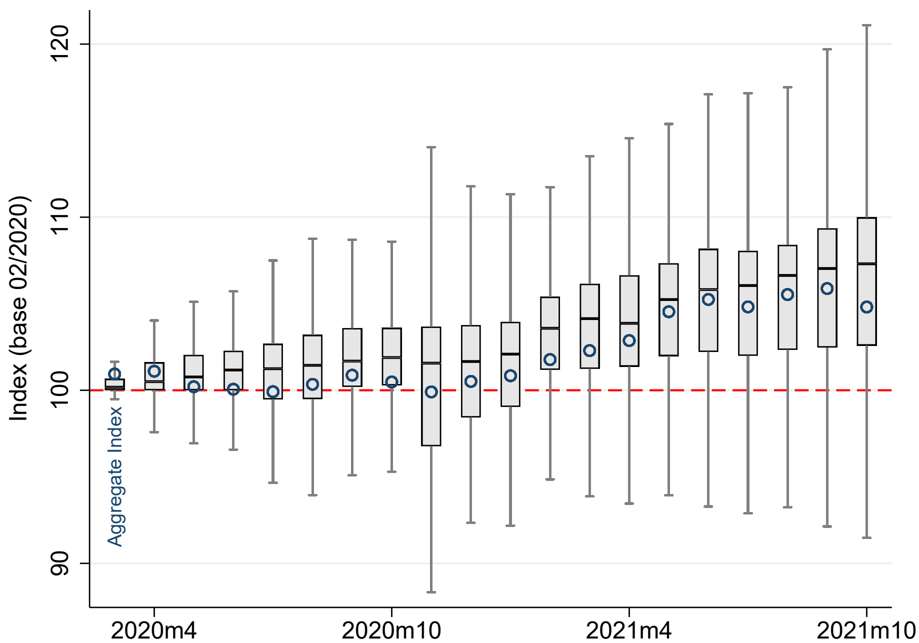
Note: Data is from Facebook. Countries include the UK, France, Spain, Italy, Switzerland, Belgium, the Netherlands, and Germany.

Figure 7: Decomposition: Import Quantities and Prices of Intermediate Goods



Note: Each data point is computed using baseline estimates for intermediate goods in Table 2 and for freight costs in Table 5 and month-specific average changes in exporter, importer and port mobility.

Figure 8: Consumer Price Index Distribution over Goods with Positive Imports by Month



Note: Each observation used to construct the box plots is an index defined at the sub-class level for which we observe positive imports. Aggregate Indices are computed by weighting the same indices by expenditure shares from the national household survey, the Encuesta Nacional de Presupuestos de los Hogares (ENPH) 2016-2017.

Table 1: The Impact of Exporter and Importer Mobility on Trade Outcomes, Baseline and Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Baseline			With Pre-trends Controls		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.433***	0.410***	0.023	0.497***	0.512***	-0.013
	(0.068)	(0.073)	(0.053)	(0.099)	(0.100)	(0.061)
Δ log exporter mobility	0.249***	0.352***	-0.103**	0.201	0.342**	-0.140**
	(0.094)	(0.124)	(0.044)	(0.129)	(0.172)	(0.067)
Fixed effects	Exporting Country-MPOE-Time & Product-Time			Exporting Country-MPOE-Time & Product-Time		
N	537,100	537,100	537,100	257,049	257,049	257,049
R^2	0.100	0.101	0.076	0.147	0.147	0.107

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B	No Product-Time Fixed Effects			No MPOE Fixed Effects		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.484***	0.415***	0.069	0.503***	0.564***	-0.060
	(0.063)	(0.070)	(0.048)	(0.070)	(0.066)	(0.041)
Δ log exporter mobility	0.232**	0.333***	-0.101***	0.138	0.225*	-0.086**
	(0.090)	(0.114)	(0.037)	(0.100)	(0.125)	(0.040)
Fixed effects	Exporting Country-MPOE-Time			Exporting Country-Time & Product-Time		
N	551,155	551,155	551,155	537,559	537,559	537,559
R^2	0.029	0.029	0.015	0.085	0.083	0.064

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C	Exporter and MPOE Fixed Effect Separability			Product-specific Transport Cost Fixed Effects		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.426***	0.416***	0.010	0.450***	0.508***	-0.058
	(0.069)	(0.072)	(0.050)	(0.099)	(0.080)	(0.065)
Δ log exporter mobility	0.189*	0.282**	-0.093**	0.525***	0.760***	-0.235***
	(0.098)	(0.125)	(0.042)	(0.138)	(0.171)	(0.061)
Fixed effects	Exporting Country-Time, MPOE-Time & Product-Time			Exporting Country-MPOE-Product-Time		
N	537,549	537,549	537,549	308,249	308,249	308,249
R^2	0.088	0.089	0.068	0.301	0.302	0.275

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. The outcome variables are at the exporter-importer-product-time level, where the product is defined at the HS6 level, and time is at the monthly frequency. Both the dependent variables and the independent variables are log changes from Feb 2020.
MPOE: Main port of entry.

Table 2: The Impact of Exporter and Importer Mobility on Trade Outcomes, by Product Categories

Panel A	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility $\times$ Consumer	0.469***	0.387***	0.082
	(0.139)	(0.149)	(0.081)
Δ log importer mobility $\times$ Intermediates	0.420***	0.393***	0.027
	(0.075)	(0.085)	(0.062)
Δ log importer mobility $\times$ Capital	0.393***	0.417***	-0.024
	(0.107)	(0.110)	(0.061)
Δ log exporter mobility $\times$ Consumer	-0.023	0.074	-0.096**
	(0.126)	(0.148)	(0.048)
Δ log exporter mobility $\times$ Intermediates	0.280***	0.398***	-0.118***
	(0.094)	(0.121)	(0.045)
Δ log exporter mobility $\times$ Capital	0.330***	0.322**	0.008
	(0.103)	(0.141)	(0.069)
N	533,312	533,312	533,312
R^2	0.100	0.101	0.077

Panel B	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.491***	0.457***	0.034
	(0.070)	(0.074)	(0.052)
Δ log importer mobility $\times$ Medical	-0.383***	-0.254	-0.128
	(0.135)	(0.156)	(0.125)
Δ log exporter mobility	0.243***	0.349***	-0.106**
	(0.094)	(0.125)	(0.046)
Δ log exporter mobility $\times$ Medical	0.302**	0.374***	-0.072
	(0.123)	(0.136)	(0.083)
N	537,100	537,100	537,100
R^2	0.100	0.101	0.076

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. The outcome variables are at the exporter-importer-product-time level, where the product is defined at the HS6 level, and time is at the monthly frequency. Both the dependent variables and the independent variables are log changes from Feb 2020. Exporting country-main port of entry-time, and product-time fixed effects are included. The definition of consumer, intermediate, and capital goods is from the BEC classification (UN). The definition of Covid-related medical goods is from the World Health Organisation and World Customs Organisation.

Table 3: The Impact of Exporter and Importer Mobility on Trade Outcomes, by Product Characteristics

Panel A	(1)	(2)	(3)	(4)
Product characteristic (C):	Upstreamness		Price stickiness	
Dependent variable:	Δ log quantity	Δ log price	Δ log quantity	Δ log price
Δ log importer mobility	0.402***	0.016	0.271***	0.018
	(0.071)	(0.051)	(0.075)	(0.046)
Δ log importer mobility × C	-0.122*	-0.033	0.262***	0.042
	(0.065)	(0.037)	(0.069)	(0.042)
Δ log exporter mobility	0.366***	-0.101**	0.359***	-0.109***
	(0.125)	(0.044)	(0.116)	(0.042)
Δ log exporter mobility × C	0.070***	0.017	0.030	0.042*
	(0.025)	(0.016)	(0.036)	(0.022)
N	530,366	530,366	486,894	486,894
R^2	0.100	0.076	0.098	0.075
Panel B	(1)	(2)	(3)	(4)
Product characteristic (C):	Inventory intensity		Differentiated	
Dependent variable:	Δ log quantity	Δ log price	Δ log quantity	Δ log price
Δ log importer mobility	0.396***	0.030	0.238***	0.083
	(0.072)	(0.050)	(0.074)	(0.056)
Δ log importer mobility × C	0.137**	0.013	0.264***	-0.092*
	(0.056)	(0.034)	(0.097)	(0.051)
Δ log exporter mobility	0.353***	-0.123***	0.359***	-0.093*
	(0.125)	(0.042)	(0.121)	(0.048)
Δ log exporter mobility × C	-0.033	0.023	-0.011	-0.014
	(0.029)	(0.024)	(0.052)	(0.026)
N	524,115	524,115	537,100	537,100
R^2	0.100	0.075	0.101	0.076

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The outcome variables are at the exporter-importer-product-time level, where the product is defined at the HS6 level, and time is at the monthly frequency. Both the dependent variables and the independent variables are log changes from Feb 2020. Exporting country-main port of entry-time, and product-time fixed effects are included. The upstreamness measure is from Antras et al. (2012), the price stickiness measure is from Nakamura and Steinsson (2008), the inventory intensity measure is from Fajgelbaum et al. (2020), and the dummy for differentiated goods is from Rauch (1999).

Table 4: The Relationship Between Port Performance Measures and Port Mobility in the Exporter Country

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: 2020 and 2021	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility, exporter country ports	-0.129**	-0.129**	0.108**	0.108**		
	(0.053)	(0.053)	(0.049)	(0.049)		
Δ log number of calls					-0.268***	-0.268***
					(0.090)	(0.090)
I (Year=2021)	0.169***		-0.021		0.149***	
	(0.021)		(0.020)		(0.018)	
Time trend		0.014***		-0.002		0.012***
		(0.002)		(0.002)		(0.002)
Constant	-0.042**	-0.106***	0.084***	0.092***	0.003	-0.052***
	(0.016)	(0.023)	(0.011)	(0.017)	(0.010)	(0.016)
Observations	492	492	492	492	492	492
R-squared	0.654	0.654	0.727	0.727	0.661	0.661
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: 2018 and 2019	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility, exporter country ports	0.018	0.018	-0.022	-0.022		
	(0.020)	(0.020)	(0.023)	(0.023)		
Δ log number of calls					-0.072	-0.072
					(0.087)	(0.087)
I (Year=2019)	0.025**		0.005		0.028***	
	(0.009)		(0.009)		(0.009)	
Time trend		0.002**		0.000		0.002***
		(0.001)		(0.001)		(0.001)
Constant	0.014**	0.005	-0.157***	-0.159***	-0.001	-0.011
	(0.006)	(0.009)	(0.007)	(0.010)	(0.016)	(0.018)
Observations	492	492	492	492	492	492
R-squared	0.749	0.749	0.883	0.883	0.749	0.749

Note: Standard errors are clustered at the exporter country level. *** p<0.01, ** p<0.05, * p<0.1. All columns control for exporter country fixed effects and calendar months fixed effects. In Panel A, the changes in the log number of hours in ports and the log number of port calls are the changes starting from March 2020 until October 2021, compared to February 2020. The mobility changes are the changes in months starting from March 2020 until October 2021, compared to the pre-Covid period, which is Feb 2020 for most countries and Jan 1-14, 2020 for China. The mean (s.d.) of mobility changes is -0.16 (0.20), the mean (s.d.) of the change in the log number of hours in port is 0.10 (0.13), and the mean (s.d.) of the change in log number of calls is -0.09 (0.11). In Panel B, the changes in the log number of hours in ports and the log number of port calls are the changes in months starting from March 2018 until October 2019, compared to February 2020. The mobility changes are the same in Panel A. The mean (s.d.) of the change in the log number of hours in port is 0.02 (0.11), and the mean (s.d.) of the change in log number of calls is -0.15 (0.14).

Table 5: The Relationship Between Freight Costs and Port Mobility in the Exporter Country

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility, exporter country ports	-0.25**	-0.25**	-0.29**	-0.53**	-0.30***	-0.30***	-0.34***	-0.57***
	(0.11)	(0.11)	(0.12)	(0.20)	(0.10)	(0.10)	(0.11)	(0.18)
I (year=2021)	0.51***		0.51***	0.54***	0.55***		0.55***	0.58***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.04***				0.05***		
		(0.01)				(0.01)		
Constant	0.02	-0.17**	0.01	-0.04	-0.04	-0.25***	-0.05	-0.09*
	(0.05)	(0.07)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
Observations	245,995	245,995	239,425	245,991	245,995	245,995	239,425	245,991
R-squared	0.11	0.11	0.16	0.11	0.15	0.15	0.20	0.16
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: 2018 and 2019	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility, exporter country ports	0.04	0.02	0.03	0.03	-0.01	0.00	-0.02	-0.04
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
I (year=2019)	0.02**		0.03**	0.03**	0.03**		0.03**	0.04**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
Time trend		0.00				0.00*		
		(0.00)				(0.00)		
Constant	0.04***	0.03***	0.04***	0.03***	-0.03***	-0.03**	-0.03***	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	261,967	261,967	255,881	261,966	261,967	261,967	255,881	261,966
R-squared	0.09	0.09	0.14	0.09	0.11	0.10	0.15	0.11
Month FE	Yes	Yes			Yes	Yes		
Product FE	Yes	Yes		Yes	Yes	Yes		Yes
Exporter country FE	Yes	Yes	Yes		Yes	Yes	Yes	
Product-month FE			Yes				Yes	
Country-month FE				Yes				Yes

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. In Panel A, The mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38), and 0.28 (0.96) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country. In Panel B, The mean (s.d.) of the change in log freight cost by unit is 0.05 (1.37), and -0.01 (0.90) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country.

Table 6: The Relationship Between Freight Costs and Port Mobility in the Exporter Country and in the Intermediate Country

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Δ log freight cost, unit			Δ log freight cost, weight		
Δ log mobility, exporter country	-0.25**			-0.30***		
	(0.11)			(0.10)		
Δ log mobility, first intermediate		-0.53***			-0.59***	
		(0.16)			(0.15)	
Δ log mobility, second intermediate			-0.72***			-0.76***
			(0.20)			(0.20)
I (year=2021)	0.51***	0.57***	0.69***	0.55***	0.62***	0.74***
	(0.08)	(0.08)	(0.11)	(0.07)	(0.08)	(0.11)
Constant	0.02	-0.06	-0.16*	-0.04	-0.12**	-0.23**
	(0.05)	(0.06)	(0.09)	(0.04)	(0.06)	(0.09)
Observations	245,995	245,995	245,995	245,995	245,995	245,995
R-squared	0.11	0.11	0.11	0.15	0.15	0.15

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. The mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38), and 0.28 (0.96) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country, -0.15 (0.16) for the first intermediate country, and -0.17 (0.20) for the second intermediate country.

Table 7: Relationship Between Import Price Increases and Consumer Price Indices.

	(1)	(2)	(3)	(4)	(5)
	Observed	Predicted	Exporter shocks	Transport prices	Exporter shock and transport prices
Δ log import price	0.013***	0.011**	0.575***	0.290	0.532***
	(0.005)	(0.006)	(0.156)	(0.193)	(0.126)
Observations	1,126	1,126	1,126	1,126	1,126
R^2	0.102	0.100	0.104	0.098	0.106

Note: Dependent variable: Consumer price index at the 5-digit CPI classification goods level. Importer prices are constructed as indicated in each column's header. All specifications include time fixed effect. Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendices

(Not for publication)

A Additional Data Descriptives

A.1 Levels of Aggregation

Table A1: Levels of aggregation and the matching results between the Facebook data and the Colombian trade data

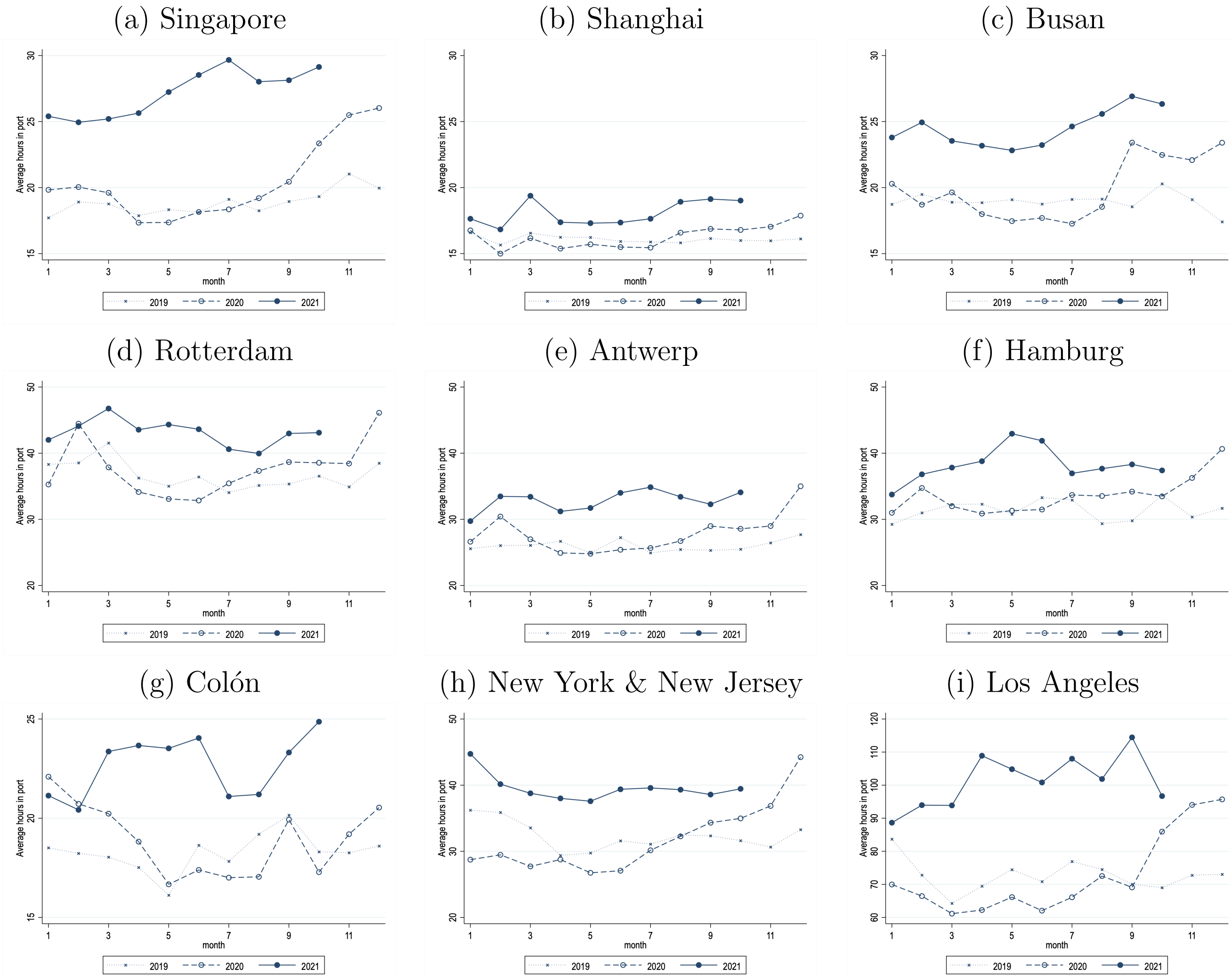
Country	Unit of geo divisions		Number of divisions						
	Colombian trade data		FB level 1	FB Level 2	Map level 1	Map Level 2	Merged	% merged	% trade
ARG	gadm 1	province	**24**	432	24	503	20	83%	100%
AUS	gadm 2	city	8	**310**	11	569	102	33%	87%
BEL	nuts 3	city		**44**		44	42	95%	99%
BOL	gadm 1	department	**9**	59	9	95	7	78%	100%
BRA	gadm 2	city/municipality	27	**3356**	27	5504	649	19%	90%
CAN	gadm 2	municipality	13	**269**	13	293	123	46%	70%
CHE	nuts 3	city		**25**		26	25	100%	99%
CHL	gadm 2	city	16	**51**	16	54	42	82%	98%
CHN	prefectures	prefecture	31	**333**	31	338	252	76%	76%
DEU	nuts 3	district		**401**		401	394	98%	99%
ECU	gadm 2	city	24	**176**	24	223	59	34%	99%
ESP	nuts 3	municipality		**59**		59	56	95%	98%
FRA	nuts 3	department		**101**		101	98	97%	96%
GBR	nuts 2	county	**41**	175	41	179	40	98%	70%
HKG	gadm 1		**1**	18	1	18	1	100%	99%
IND	gadm 2	district	36	**658**	36	666	193	29%	75%
ITA	nuts 3	city		**110**		107	105	95%	97%
JPN	gadm 1	prefecture	**47**	690	47	1811	35	74%	100%
KOR	gadm 2	province	**17**	224	17	229	17	100%	100%
MEX	gadm 2	municipality	32	**1111**	32	1854	220	20%	93%
NLD	nuts 3	COROP regions		**40**		40	39	98%	98%
PAN	gadm 2	district	9	**25**	13	79	13	52%	99%
PER	gadm 2	city	26	**151**	26	195	47	31%	98%
TWN	gadm 2	county/city	7	**22**	7	22	17	77%	96%
URY	gadm 1	department	**19**	71	17	204	15	79%	100%
USA	place		56	**2693**	56	3233	1232	46%	75%
VNM	gadm 1		**63**	707	63	710	38	60%	100%

A.2 Ports Included in the Analysis

Table A2: The 150 ports used in the analysis, with TEU in 2019 (millions)

Country	Port	TEU (in millions)	Country	Port	TEU (in millions)	Country	Port	TEU (in millions)
ARG	Buenos Aires	3.93	DEU	Hamburg	17.83	JPN	Nagoya	8.38
AUS	Adelaide	2.27	ECU	Posorja	0.48	JPN	Kobe	8.98
AUS	Fremantle	2.47	ECU	Puerto Bolivar (Ecuador)	0.50	JPN	Tokyo	12.15
AUS	Brisbane	4.45	ECU	Guayaquil	3.50	JPN	Yokohama	12.54
AUS	Melbourne	4.74	ESP	Cartagena (Spain)	0.13	KOR	Gunsan	0.21
AUS	Port Botany	5.15	ESP	Sagunto	0.30	KOR	Pyeong Taek	0.74
BEL	Zeebrugge	1.94	ESP	Tarragona	0.31	KOR	Ulsan	2.47
BEL	Antwerp	22.10	ESP	Gijon	0.33	KOR	Incheon	4.26
BRA	Vila do Conde	0.36	ESP	Alicante	0.35	KOR	Yosu	10.27
BRA	Vitoria	0.40	ESP	Vigo	0.69	KOR	Busan	50.47
BRA	Manaus	0.66	ESP	Bilbao	0.70	MEX	Ensenada	2.00
BRA	Pecem	1.69	ESP	Castellon	1.07	MEX	Altamira	2.86
BRA	Sepetiba	1.70	ESP	Malaga	1.20	MEX	Veracruz	3.10
BRA	Suape	2.25	ESP	Barcelona	9.99	MEX	Lazaro Cardenas	4.28
BRA	Salvador	3.05	ESP	Algeciras	13.46	MEX	Manzanillo (Mexico)	8.70
BRA	Rio Grande (Brazil)	3.39	ESP	Valencia	14.70	NLD	Moerdijk	0.45
BRA	Rio de Janeiro	3.84	FRA	Nantes-St Nazaire	0.51	NLD	Vlissingen	0.61
BRA	Itapoa	3.99	FRA	Dunkirk	1.87	NLD	Rotterdam	32.24
BRA	Paranagua	5.58	FRA	Marseille	6.09	PAN	Balboa	5.12
BRA	Itajai	5.87	FRA	Le Havre	13.98	PAN	Colon	14.71
BRA	Santos	11.75	GBR	London Thamesport	0.11	PER	Paita	0.55
CAN	Halifax	1.45	GBR	Belfast	0.22	PER	Callao	7.70
CAN	Montreal	1.55	GBR	Greenock	0.23	SGP	Singapore	80.99
CAN	Prince Rupert	1.98	GBR	Bristol	0.24	TWN	Keelung	4.97
CAN	Vancouver (Canada)	5.02	GBR	Grangemouth	0.28	TWN	Taipei	6.04
CHL	Arica	0.62	GBR	Immingham	0.39	TWN	Kaohsiung	29.72
CHL	San Vicente	0.90	GBR	Hull	0.42	URY	Montevideo	3.66
CHL	Lirquen	1.00	GBR	Teesport	0.67	USA	Palm Beach	0.17
CHL	Iquique	1.06	GBR	Liverpool (United Kingdom)	1.53	USA	Wilmington (USA-Delaware)	0.32
CHL	Mejillones	1.21	GBR	Southampton	6.16	USA	Eddystone	0.36
CHL	Coronel	1.65	GBR	London	9.05	USA	Wilmington (USA-N Carolina)	1.29
CHL	Valparaiso	2.07	GBR	Felixstowe	9.29	USA	Philadelphia	2.36
CHL	San Antonio	4.17	HKG	Hong Kong	46.39	USA	Baltimore (USA)	2.55
CHN	Dalian	8.55	IND	Tuticorin	1.07	USA	Tacoma	2.72
CHN	Guangzhou	11.59	IND	Cochin	1.88	USA	New Orleans	2.72
CHN	Tianjin	19.61	IND	Jawaharlal Nehru Port	9.85	USA	Port Everglades	2.96
CHN	Xiamen	21.51	ITA	Bari	0.11	USA	Miami	3.57
CHN	Qingdao	31.69	ITA	Catania	0.15	USA	Seattle	3.57
CHN	Shenzhen	64.32	ITA	Ancona	0.61	USA	Houston	5.05
CHN	Ningbo	65.36	ITA	Ravenna	0.62	USA	Savannah	5.43
CHN	Shanghai	74.67	ITA	Salerno	1.18	USA	Los Angeles	7.35
COL	Barranquilla	0.50	ITA	Venice	1.19	USA	Long Beach	8.00
COL	Turbo	0.51	ITA	Naples	1.75	USA	Port of Virginia	8.37
COL	Santa Marta	0.51	ITA	Trieste	2.30	USA	Charleston	9.24
COL	Aguadulce (Colombia)	1.62	ITA	Livorno	3.16	USA	Oakland	9.99
COL	Buenaventura	3.30	ITA	La Spezia	5.20	USA	New York & New Jersey	13.40
COL	Cartagena (Colombia)	8.24	ITA	Gioia Tauro	6.43	VNM	Quy Nhon	0.57
DEU	Lubeck	0.10	ITA	Genoa	8.95	VNM	Danang	1.53
DEU	Wilhelmshaven	3.36	JPN	Shimizu	2.74	VNM	Saigon	2.93
DEU	Bremerhaven	12.66	JPN	Osaka	5.72	VNM	Haiphong	5.26

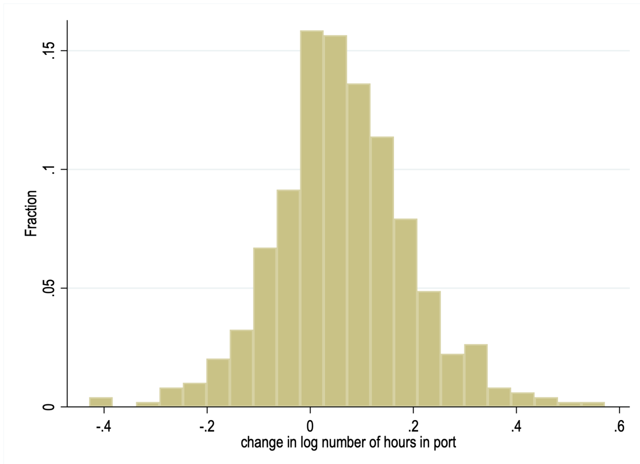
Figure A1: Average Hours in Port, 9 Important Ports



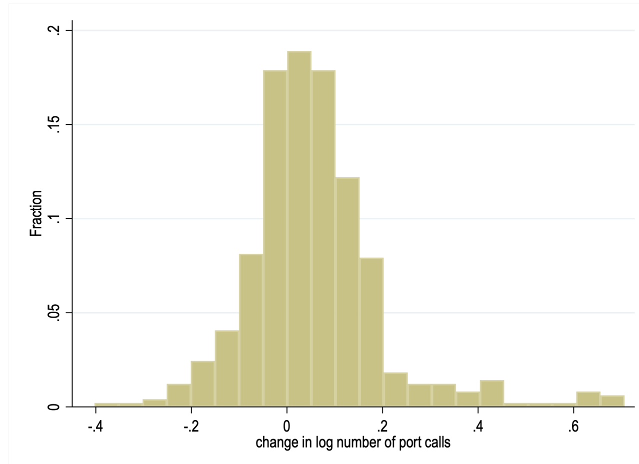
Note: Data is from the IHS Markit Maritime & Trade Platform. The hours in port are measured as the difference between the sailed time and the arrival time at the port.

Figure A2: The Histogram of Country-Level Port Performance Variation

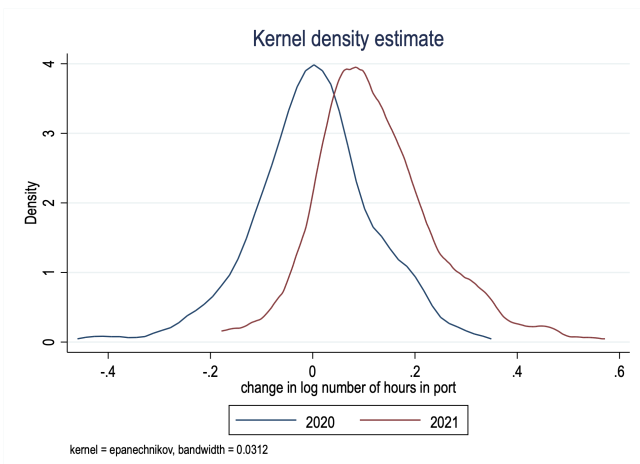
(a) Changes in log number of hours in port
March 2020 to October 20201



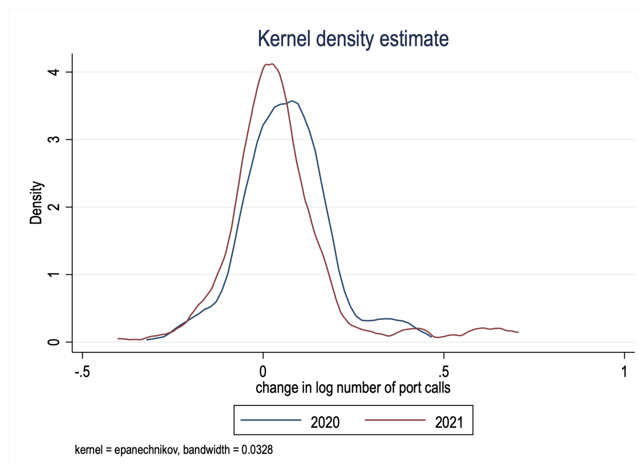
(b) Changes in log number of port calls
March 2020 to October 20201



(c) Changes in log number of hours in port
2020 versus 2021



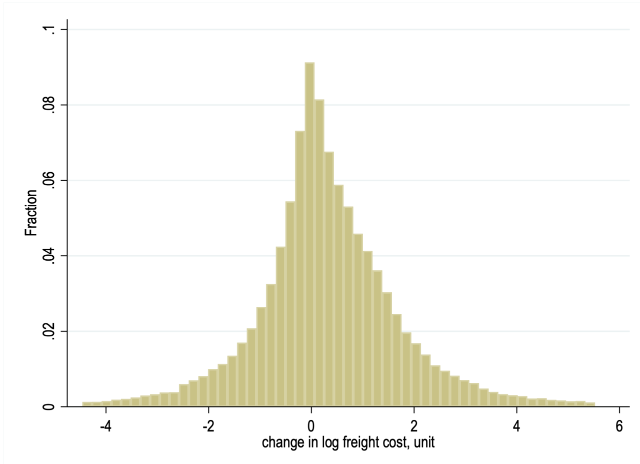
(d) Changes in log number of port calls
2020 versus 2021



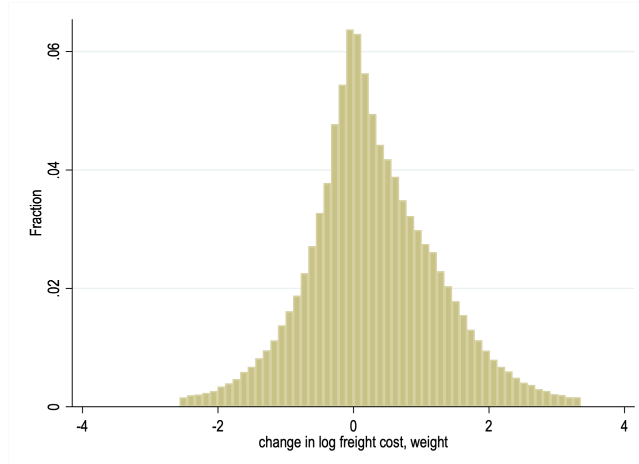
Note: Panels (a) and (b) are the histograms of the changes in port performance in the post-Covid period (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and in 2021 separately, using kernel densities.

Figure A3: The Histogram of Product-Level Freight Cost Variation

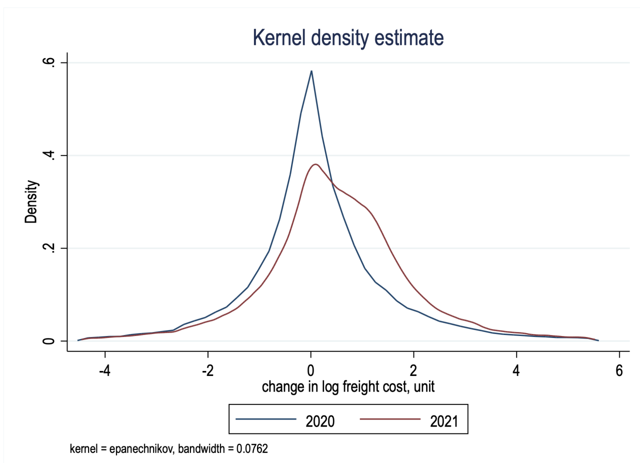
(a) Changes in log freight cost, unit
March 2020 to October 20201



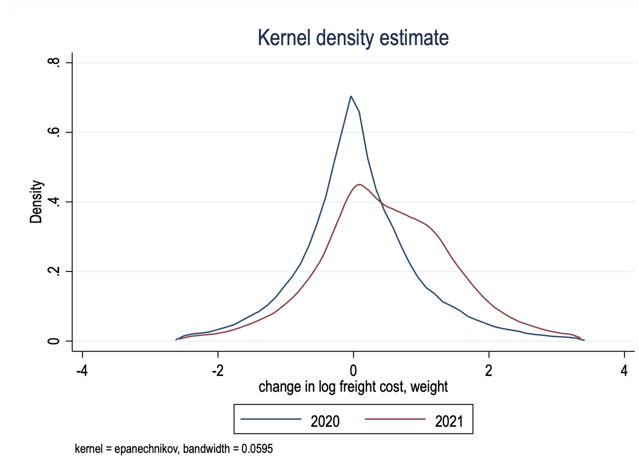
(b) Changes in log freight cost, weight
March 2020 to October 20201



(c) Changes in log freight cost, unit
2020 versus 2021



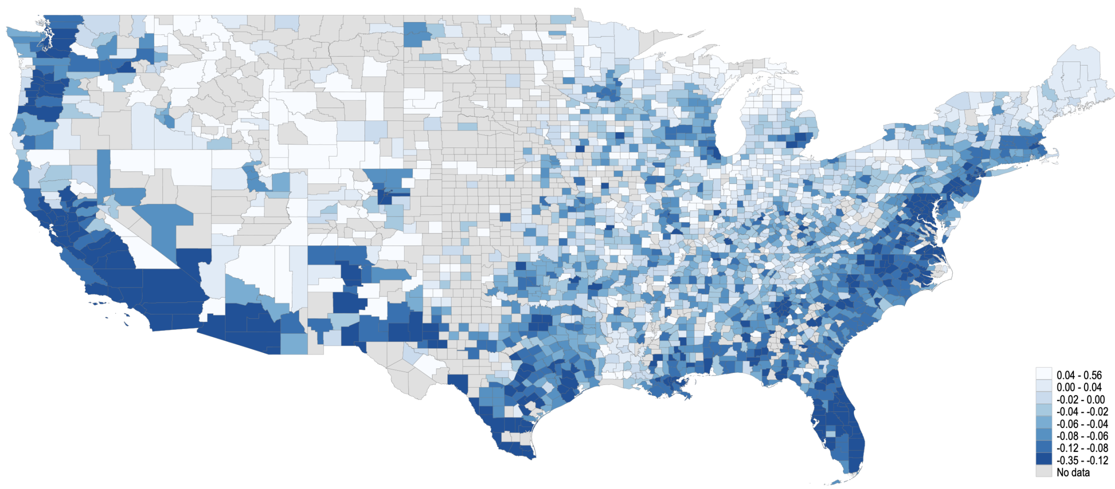
(d) Changes in log freight cost, weight calls
2020 versus 2021



Note: Panels (a) and (b) are the histograms of the changes in log freight cost in the post-Covid period (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and in 2021 separately, using kernel densities. Panels (a) and (c) do not include the changes in log freight costs (unit) in the top 1% and the bottom 1% of the distribution. Panels (b) and (d) do not include the changes in log freight costs (weight) in the top 1% and the bottom 1% of the distribution.

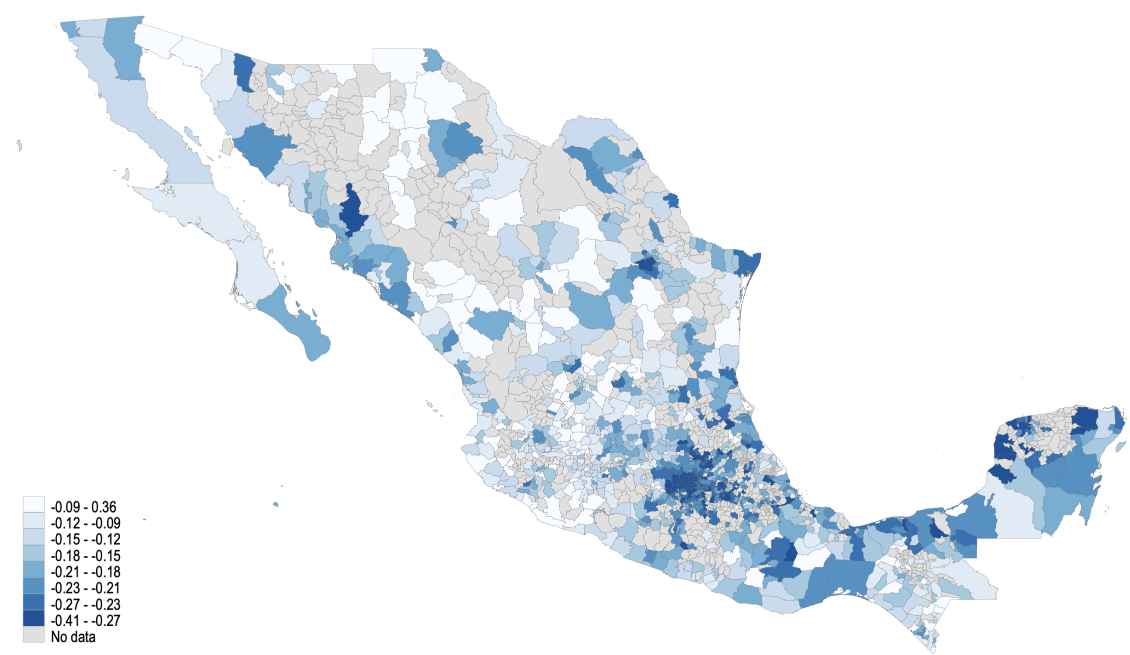
A.3 Mobility Change Maps

Figure A4: The decline in mobility across NUTS3 units in the US, September 2020



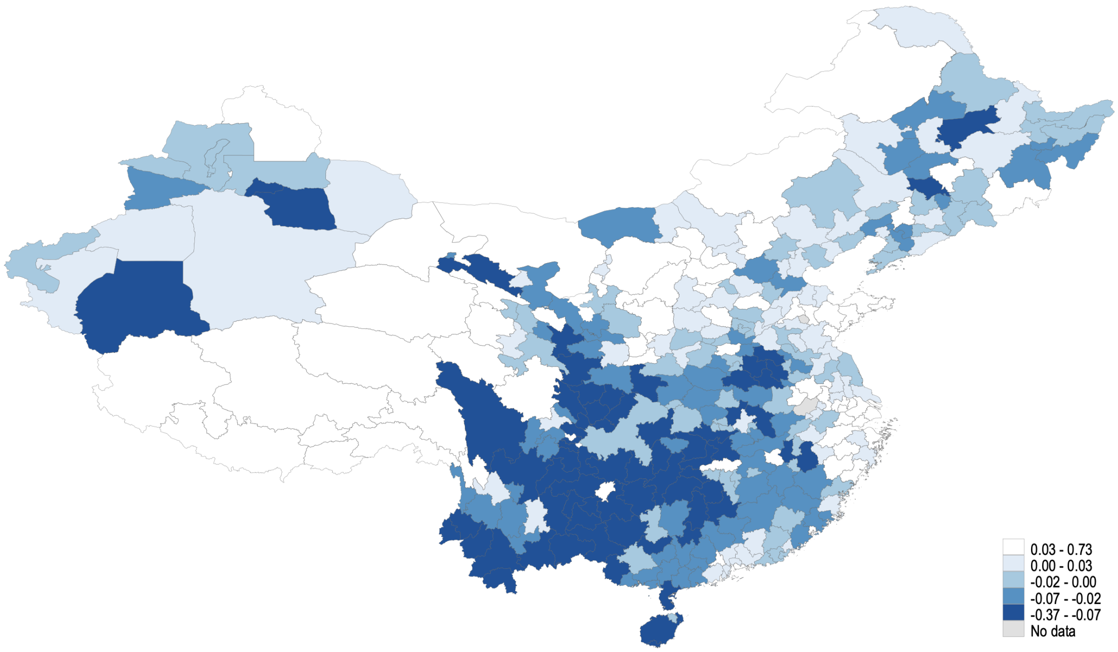
Note: Data is from Facebook.

Figure A5: The decline in mobility across *municipios* in Mexico, September 2020



Note: Data is from Facebook.

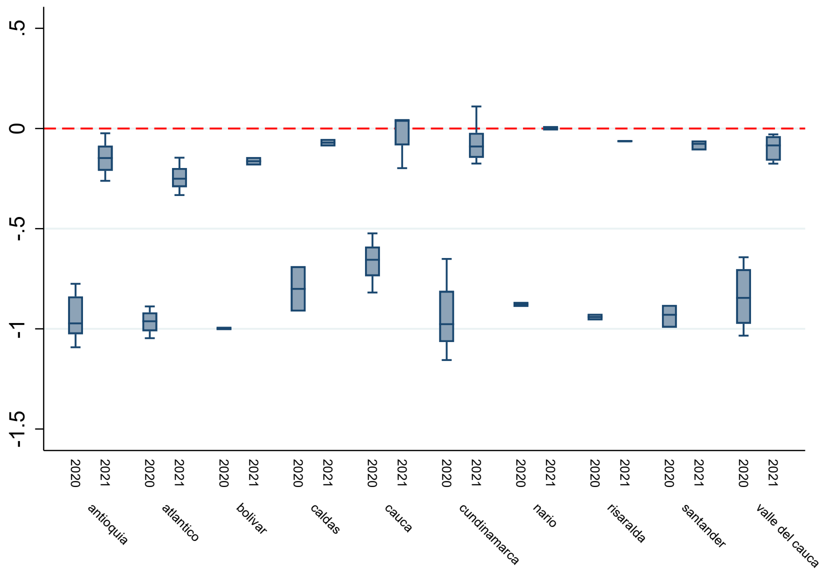
Figure A6: The decline in mobility across prefectures in China, September 2020



Note: Data is from Baidu.

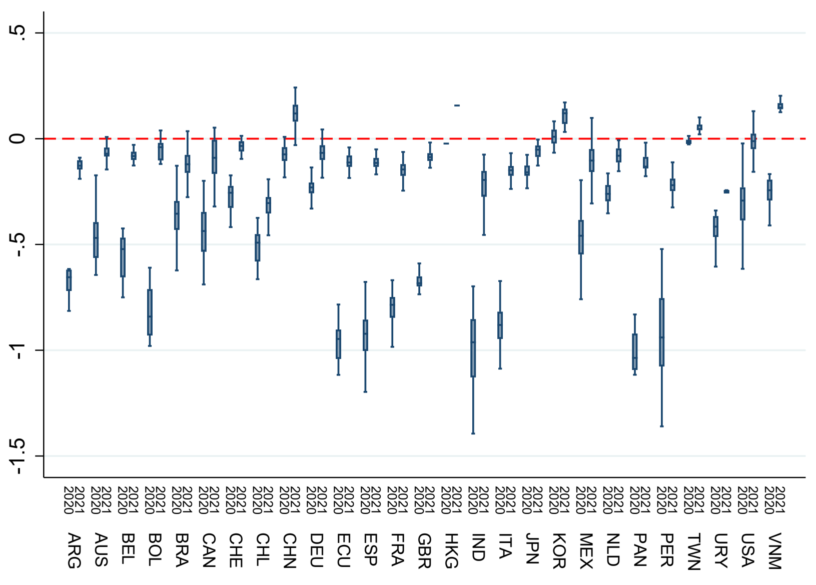
A.4 Mobility Variation at Colombia and Exporting Countries

Figure A7: Change in Average Importer Mobility by Colombian Department. April 2020 and April 2021



Note: Each observation is a municipality-month log change in importer mobility with respect to February 2020. Only departments of the top 60 municipalities in terms of 2018-2019 imports included.

Figure A8: Change in Average Exporter Mobility by Country. April 2020 and April 2021



Note: Each observation is a exporter city-month log change in exporter mobility with respect to February 2020.

A.5 Descriptive Statistics of Variables Used in Baseline Exporter and Importer Shocks Regressions

Table A3: Descriptive Statistics of Variables Used in Baseline Exporter and Importer Shocks Regressions

Variable	Mean	sd	Q1	Median	Q3	N
Baseline Sample						
Δ log Import Values	-0.076	1.822	-1.008	-0.031	0.861	537100
Δ log Import Quantities	-0.117	2.032	-1.099	-0.029	0.857	537100
Δ log Import Prices	0.041	1.342	-0.347	0.021	0.429	537100
Δ log Importer Mobility	-0.250	0.264	-0.340	-0.171	-0.082	537100
Δ log Exporter Mobility	-0.135	0.182	-0.211	-0.118	-0.021	537100
Δ log Congestion $\hat{D}$	-0.264	0.205	-0.346	-0.235	-0.117	486090
Δ log Congestion $\hat{S}$	-0.226	0.203	-0.329	-0.183	-0.074	486090
Consumption Goods Sample						
Δ log Import Values	-0.138	1.759	-1.054	-0.084	0.783	105270
Δ log Import Quantities	-0.192	1.986	-1.174	-0.118	0.788	105270
Δ log Import Prices	0.055	1.116	-0.246	0.021	0.330	105270
Δ log Importer Mobility	-0.243	0.251	-0.325	-0.170	-0.082	105270
Δ log Exporter Mobility	-0.141	0.189	-0.222	-0.121	-0.029	105270
Intermediate Goods Sample						
Δ log Import Values	-0.060	1.831	-0.979	-0.016	0.864	329990
Δ log Import Quantities	-0.095	2.065	-1.082	-0.011	0.875	329990
Δ log Import Prices	0.034	1.355	-0.364	0.021	0.439	329990
Δ log Importer Mobility	-0.251	0.267	-0.354	-0.170	-0.079	329990
Δ log Exporter Mobility	-0.136	0.182	-0.210	-0.118	-0.019	329990
Capital Goods Sample						
Δ log Import Values	-0.052	1.862	-1.053	-0.027	0.954	98068
Δ log Import Quantities	-0.095	1.952	-1.099	0.000	0.894	98068
Δ log Import Prices	0.043	1.505	-0.452	0.020	0.543	98068
Δ log Importer Mobility	-0.254	0.265	-0.349	-0.183	-0.082	98068
Δ log Exporter Mobility	-0.125	0.171	-0.206	-0.113	-0.013	98068
Extensive Margin Sample						
$\Delta I(\text{Imports} > 0)$	-0.012	0.373	0.000	0.000	0.000	10888687
Δ log Importer Mobility	-0.250	0.274	-0.374	-0.163	-0.066	10888687
Δ log Exporter Mobility	-0.130	0.192	-0.203	-0.103	-0.012	10888687
Δ log Congestion $\hat{D}$	-0.268	0.210	-0.347	-0.234	-0.120	9576852
Δ log Congestion $\hat{S}$	-0.226	0.206	-0.328	-0.181	-0.074	9576852

A.6 Congestion Variables

A.6.1 Supply-side Congestion

An exporter serving two locations may see an increase in demand from one of them, and given it cannot expand its capital, the result is higher marginal costs of production and prices for both importing locations. This is the first, supply-side source of congestion, which we proxy as follows:

$$\hat{S}_{ckt} = \sum_{\tilde{c} \in C|c} s^{2018}_{X,\tilde{c}k} \hat{x}_{\tilde{c}t}, \tag{26}$$

where $s^{2018}_{X,\tilde{c}k}$ are the exporter share of country $\tilde{c}$ in world trade of product k in 2018, and $\hat{x}_{\tilde{c}t}$ is the country-level mobility change at t.[39] We interpret a decrease in this measure as an indication of an increase in demand for exporter j, conditional on the pandemic shock at that location. [40]

A.6.2 Demand-side Congestion

Suppose only two locations import a given product and one of them experiences a mobility shock associated with the pandemic. The effect on the importing price and demand of the other location depends on the nature of the shock—e.g. whether the income or substitution effect dominates. We proxy for this mechanism as follows:

$$\hat{D}_{ckt} = \sum_{\tilde{c} \in C|c} s^{2018}_{M,\tilde{c}k} \hat{x}_{\tilde{c}t}, \tag{27}$$

where $s^{2018}_{M,\tilde{c}k}$ are the importer share of country $\tilde{c}$ in world trade of product k in 2018.

[39] Mobility data at country level from Google.

[40] In terms of the model, the degree to which demand shifts due to congestion shocks depends on η^K.

A.7 Descriptive Statistics of Consumer Price Indices

Figure A9: Aggregate Consumer Price Index for Goods Sub-classes with and without Matched Imports

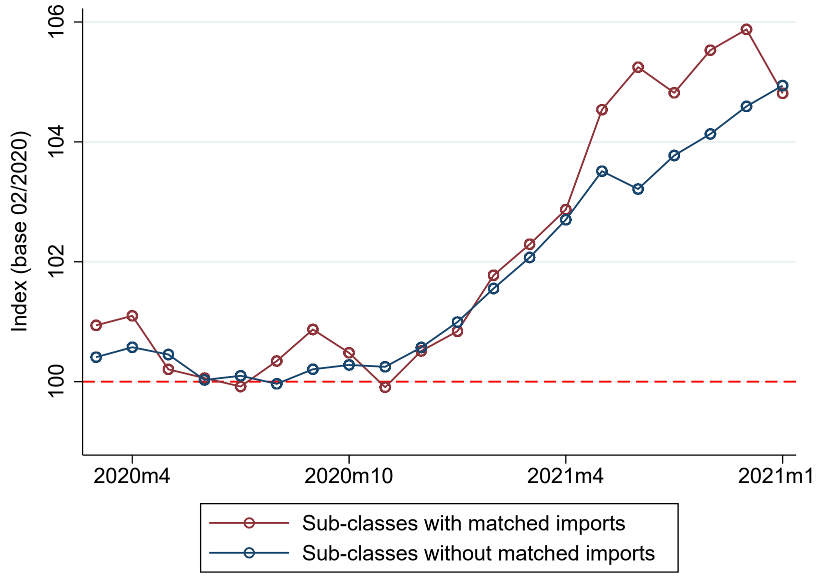
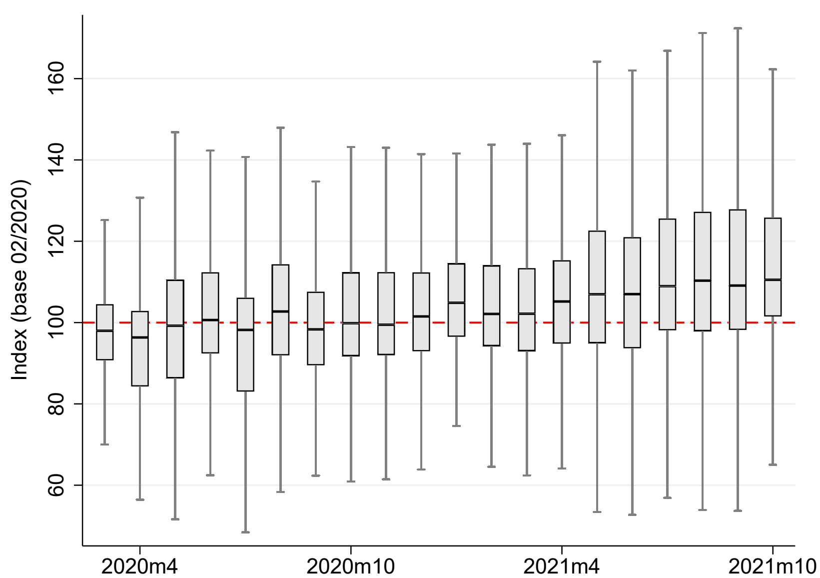


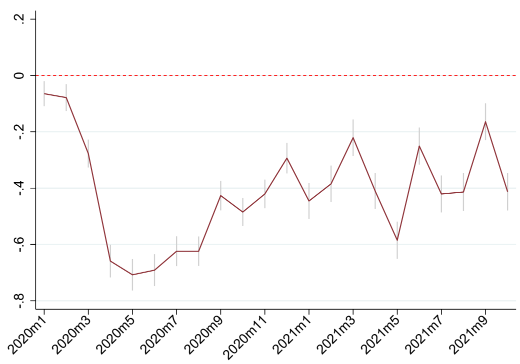
Figure A10: Import Price Index Distribution over Goods with Positive Imports by Month



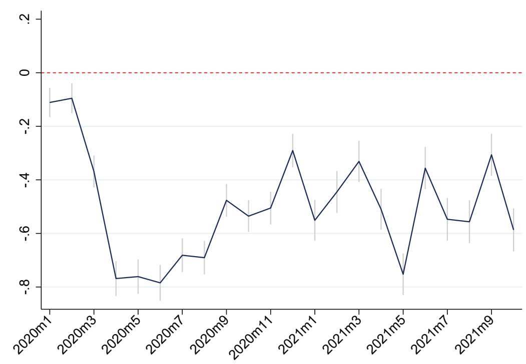
B Additional Empirical Results

B.1 Trade Trends for the Balanced Sample

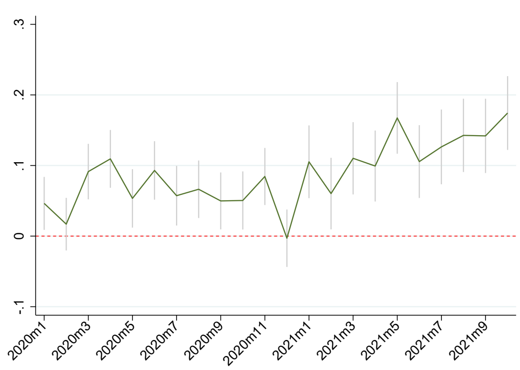
Figure B1: Average Change in Import Variables Relative to Pre-Pandemic Trends, Balanced Sample



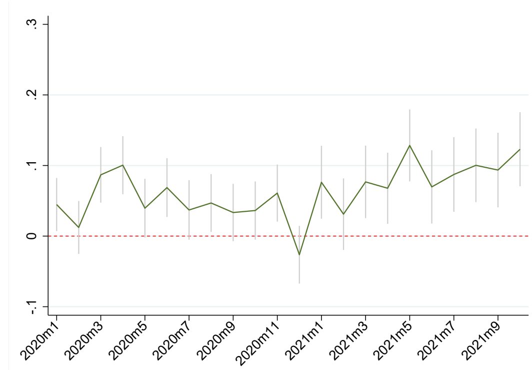
(a) Import Values (m)



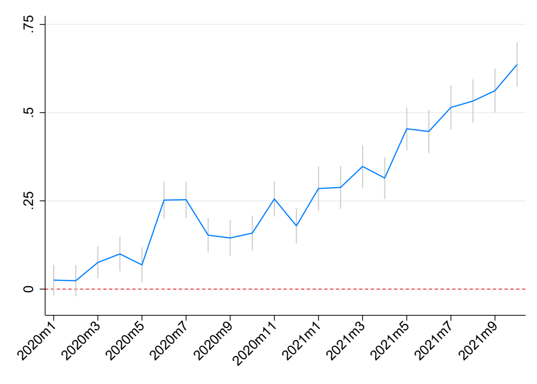
(b) Import Quantities (q)



(c) Importer Prices (p^X)



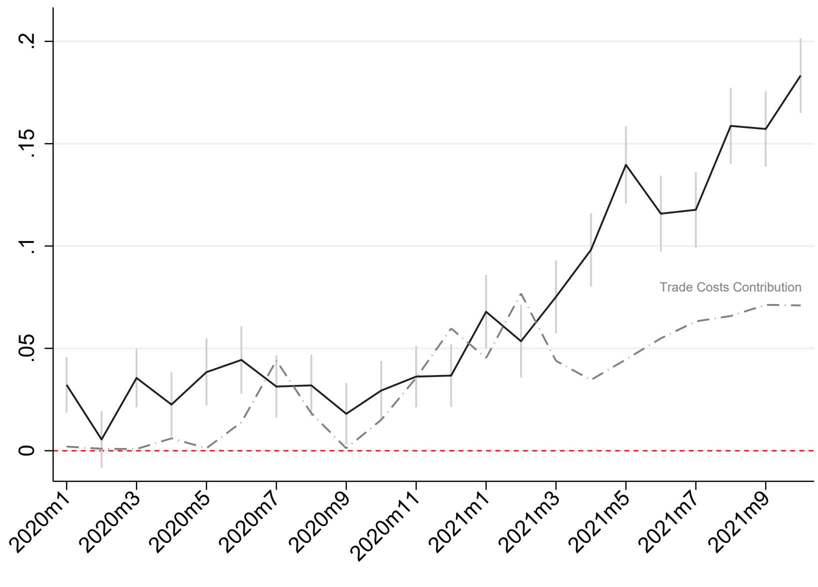
(d) Exporter prices



(e) Freight cost

Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals, using the balanced sample only. Standard errors clustered at the exporter-importer-product level.

Figure B2: Average Change in Import Prices Relative to Pre-Pandemic Trends



Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals. Standard errors clustered at the exporter-importer-product level. Contribution of trade costs calculated as the share of pre-pandemic trade costs (0.08) times the estimated change of freight and insurance unit value in Figure 2.

B.2 Validation of the Mobility Measure

In this section, we provide evidence of the relationship between mobility changes, local covid outbreak, and policies.

In this paper, we use the observed mobility changes as an aggregate measure which captures the reduction in economic activity. The mobility reduction can be the result of the increased risks of infection and the associated policies that intend to contain the spread of the virus. On the other hand, a reduction in local mobility can in turn affect the rate of infection and policy, both through the reduction in human contact and the associated reduction in income. Thus, it is difficult to identify the causal relationship between observed mobility change, observed number of cases, and government containment policies. We don't intend to uncover this highly dynamic relationship and focus on documenting the association between them to show that in regions with larger reductions in mobility, they also have larger numbers of cases and more stringent policy.

We use the national level Covid-19 policies from Hale et al. (2021) and the daily number of new cases for European NUTS3 regions from March 2020 to August 2021 by Asjad (2021). We use the eight European countries (i.e., Belgium, Switzerland, Germany, Spain, France, UK, Italy, and the Netherlands) because of easy data access and sufficient variation at the sub-national level (in cases) and at the national level (in policy). In addition, except for the UK, the unit of analysis here will be the same as in the main regressions (i.e., period-city, where a period is a month in a particular year). Both the data on cases and on government policies are on a daily basis, and we compute the average of each measure over a period.

Table B1: The Relationship between the mobility change and the number of new cases.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Δ log mobility					
Average daily new cases	-0.111***	-0.150***	-0.018***	-0.009**	-0.046***	-0.036***
(per 1000 persons)	(0.007)	(0.007)	(0.005)	(0.004)	(0.006)	(0.003)
Constant	-0.091***	-0.086***	-0.103***	-0.104***	-0.099***	-0.101***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	16,443	16,443	16,443	16,443	16,443	16,443
R-squared	0.012	0.593	0.742	0.787	0.933	0.978
Period FE	-	Y	Y	Y	-	-
Country FE	-	-	Y	-	-	-
Region FE	-	-	-	Y	-	Y
Country-Period FE	-	-	-	-	Y	Y

Note: Robust standard errors clustered at the importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B1 presents the correlation between changes in log mobility at the region level and the average daily new cases. Column (1) shows that an increase in infection rate by one case per thousand population is associated with a 11 percent larger mobility decline. Columns (2) to (6) include various fixed effects, and the effect ranges from 1 percent to 15 percent depending on the specification. Our preferred specification is Column (6), where both region fixed effects and country-period fixed effects are included. This specification allows different regions to have different mobility declines with zero cases, and control for policy changes at the country period level. Thus, we are using the variation within countries.

Table B2 presents the results on policy effects. Since the policy data is only available at the country-period level, we only include region fixed effects and period fixed effects, as in Column (4) Table B1. Column (1) shows the relationship between the stringency index and the log change in mobility. The mean (s.d.) of the stringency index is 65 (12), thus a one-standard deviation increase in the stringency index is associated with a 8.4 percent larger decline in mobility. The coefficient remains similar when controlling for the number of cases in Column (2). Columns (3) and (4) use alternative measures of stringency index, which are government response index and containment health index, and both indices have a similar relationship with the mobility change. Column (5) uses the economic support index, and there is a positive association. Unlike the government response index and the containment health index, the economic support index is not highly correlated with the overall stringency index.

Overall, we find that a larger number of local cases and a more stringency government containment policy are associated with a larger decline in mobility. Thus, the mobility change we use does capture Covid-related reactions.

Table B2: The Relationship between the mobility change and containment policies.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Δ log mobility				
StringencyIndex	-0.007***	-0.007***			
	(0.000)	(0.000)			
GovernmentResponseIndex			-0.008***		
			(0.000)		
ContainmentHealthIndex				-0.009***	
				(0.000)	
EconomicSupportIndex					0.003***
					(0.000)
Average daily new cases		-0.034***	-0.022***	-0.028***	-0.013***
(per 1000 persons)		(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.361***	0.369***	0.395***	0.452***	-0.262***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.008)
Observations	16,445	16,443	16,443	16,443	16,443
R-squared	0.855	0.856	0.822	0.839	0.803

Note: All columns include region fixed effects and period fixed effects Robust standard errors in parentheses. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

B.3 Effects of Mobility Changes Aggregated at the Importer and Exporter City

B.3.1 Effects of Mobility Changes at the Importer City

Colombia is divided into 32 departments and about 1,100 municipalities. We employ the top 60 municipalities in terms of 2018–2019 imports for the analysis, which explain about 99% of total imports. In Appendix Figure A7, we plot the distribution of mobility shocks relative to February 2020 in April 2020 — the month with the highest reduction in mobility — and in April 2021, by the department of those included. As observed, there is a variation within departments and over time.

In order to explore the relationship between importer mobility and import values, we estimate the following equation at the monthly frequency:

$$\hat{m}_{jt} \quad = \quad \beta^J \hat{x}^J_{jt} + \tilde{\mathbf{\Theta}}^J + \varepsilon_{jt}, \tag{28}$$

where $\hat{m}_{jt}$ is the log change in imports in location j at t relative to February 2020, and $\hat{x}^J_{jt}$ is the log change in importer mobility in j at t relative to February 2020. The term $\tilde{\mathbf{\Theta}}^J$ is a vector of fixed effects, specified below, and ε_{jt} is an idiosyncratic error term. The sample period runs from March 2020 to October 2021.

The coefficient of interest is β^J, which we interpret as the correlation between importer mobility and import values at the importer-level. It is reasonable to expect β^J to be positive, since a reduction in mobility during the pandemic can be associated with a local covid shock —either through a lockdown or self-isolation due to an increase in covid cases—, which can reduce consumer and firms' demand for imported goods through a decline in economic activity.

In the top panel of Table B3, we estimate Equation 28 for different fixed effects specifications. In column (1), we include month fixed effects to control for seasonal demand factors. The impact of changes in mobility is positive and significant as expected. A 10% decrease in local mobility relative to February 2020 is related to a 8.8% decrease in import values. Including year fixed effect in column (2) reduces the effect to about 4.3%, suggesting a higher elasticity for inter-annual changes in mobility during the pandemic. In column (3), we introduce time (i.e., month-year) fixed effects, to see if variation in mobility across locations at a given time also affects import values. The impact is positive and significant. In columns (4) to (6), we replicate Columns (1) to (3) but also add department fixed effects. Estimates remain positive but become noisier when we include year or time fixed effects. Figure B3 presents the residual plot corresponding to Column (3) in Table B3 and shows that the result is not driven by outliers in either the mobility or the import variables.

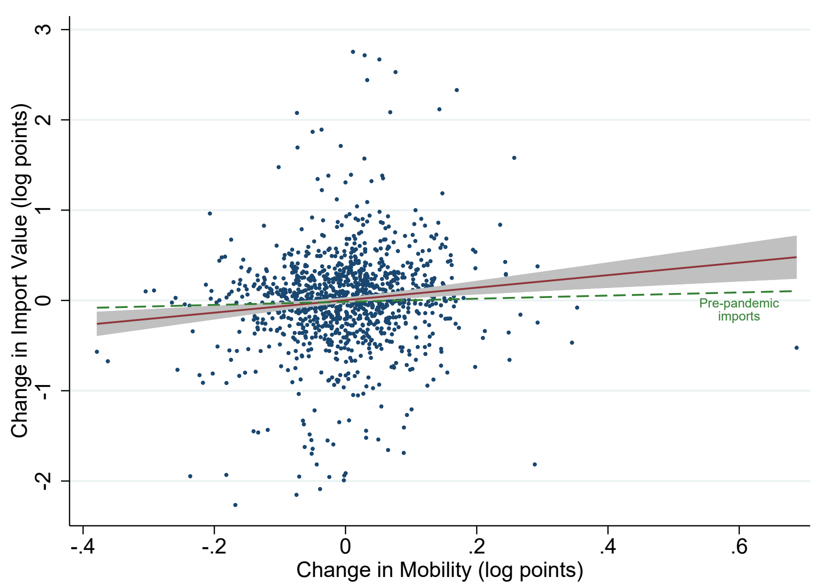
In the bottom panel of Table B3, we explore whether changes in mobility can be associated to the existence pre-pandemic trends. To do so, we regress changes in import values for 2018–2019 period relative to February 2018, i.e., before the pandemic, on changes in mobility during the pandemic. We estimate the same specifications as in the top panel and all estimates are insignificant. We interpret this as providing support to the exogeneity of the variation we employ during the baseline period. In Figure B3 we also include the residual linear fit of Column (3) specification in the bottom panel of Table B3.

Table B3: The Relationship Between Importer Local Mobility and Import Values

	(1)	(2)	(3)	(4)	(5)	(6)
Imports in the Pandemic period (2020-2021)						
Δ log Importer Mobility (2020-2021)	0.879***	0.429***	0.692***	0.837***	0.208	0.349
	(0.079)	(0.129)	(0.197)	(0.074)	(0.129)	(0.228)
Department F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155
R^2	0.120	0.132	0.139	0.255	0.274	0.278
Imports in the Pre-pandemic period (2018-2019)						
Δ log Importer Mobility (2020-2021)	0.029	0.072	0.173	0.015	0.021	0.110
	(0.061)	(0.105)	(0.153)	(0.051)	(0.103)	(0.169)
Department F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155
R^2	0.016	0.016	0.020	0.348	0.348	0.352

Note: OLS regressions at importer location-time level, where time is at the monthly frequency. Fixed effects are included as indicated in each column. Robust standard errors clustered at the importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Figure B3: Residual Plot for the Impact of Importer Mobility on Import Values



Note: Residual plot of equation 28 with period fixed effects (Column (3) of Table B3). Pandemic period fit (red solid line): $\hat{m}^{resid}_{ct} = 0.003 + 0.692 *** \times \hat{x}^{I,resid}_{ct}$. Pre-pandemic period (green dash line): $\hat{m}^{resid}_{jt} = -0.015 + 0.173 \times \hat{x}^{J,resid}_{jt}$.

In sum, mobility declines at the importer location during the pandemic are associated with lower imports from that location as expected. Those declines are not observed when we employ pre-pandemic import changes.

B.3.2 Effects of Mobility Changes at the Exporter City

We analyze the impact of local exporter mobility on Colombian imports using the 26 main partners of Colombia, excluding Venezuela.[41] In total, these countries provide about 4,200 locations where we can identify local mobility shocks. In Appendix Figure A8, we plot the distribution of mobility shocks in April 2020 and in April 2021 by country, both relative to February 2020. The figure shows that there is variation over time and within countries in exporter mobility shocks.

We estimate the correlation of exporter mobility and imports originating at that location using the following empirical equation:

$$\hat{m}_{it} = \beta^I \hat{x}_{it}^I + \tilde{\boldsymbol{\Theta}}^I + \varepsilon_{it}, \tag{29}$$

where $\hat{m}_{it}$ is the log change in Colombian imports from i at t relative to February 2020, and $\hat{x}_i^I$ is the log change in exporter mobility in i at t relative to February 2020. The term $\tilde{\boldsymbol{\Theta}}^I$ is a vector of fixed effects, specified below, and ε_{it} is an idiosyncratic error term. The sample period runs from March 2020 to October 2021, with the exception of Chinese locations, which runs from March 2020 to May 2020 and from September 2020 to May 2021 due to mobility data availability.

The coefficient of interest is β^I, which reflects the effect of exporter mobility changes on the value of imports. We expect β^I to be positive since a reduction in mobility in an exporter city can reflect a local covid shock and likely higher costs of production and shipping.

We estimate Equation 29 for different fixed effect specifications in the top panel of Table B4. In column (1), we include month fixed effects to control for seasonal supply factors. The impact of changes in mobility is positive and significant as expected. A decrease of 10% in exporter mobility is related to a decrease of 3.4% in imports from that location. This estimate is lower than what we observed on the importer mobility side. Including year or time fixed effects in Columns (2) and (3) make the estimate insignificant, suggesting that time variation is a key driver of the impact.

The definition of a location differs across countries and thus cross-countries comparisons can capture differences in sizes.[42] Therefore, we replicate estimations in columns 1 to 3 and add country fixed effects. Estimates in columns (4) to (6) are qualitatively the same, but relatively less noisy. When we include country and month fixed effects, a decrease of 10% in exporter mobility is related to a decrease of 4.7% in import values from there.

We show the residual plot associated to specification in column (4) of the top panel in Table B4 in Figure B4. We average residuals to the exporting country and time level to

[41] We do not include Venezuela, one of the main Colombian partners, due to the lack of mobility data.

[42] For instance, we use a 1-digit GADM (Database of Global Administrative Areas) classification for Argentina, but a 2-digit GADM classification for Australia. We chose the level of aggregation based on how the exporter location was declared in the Colombian imports data. See details in Table A1.

Table B4: The Relationship Between Exporter Local Mobility and Import Values

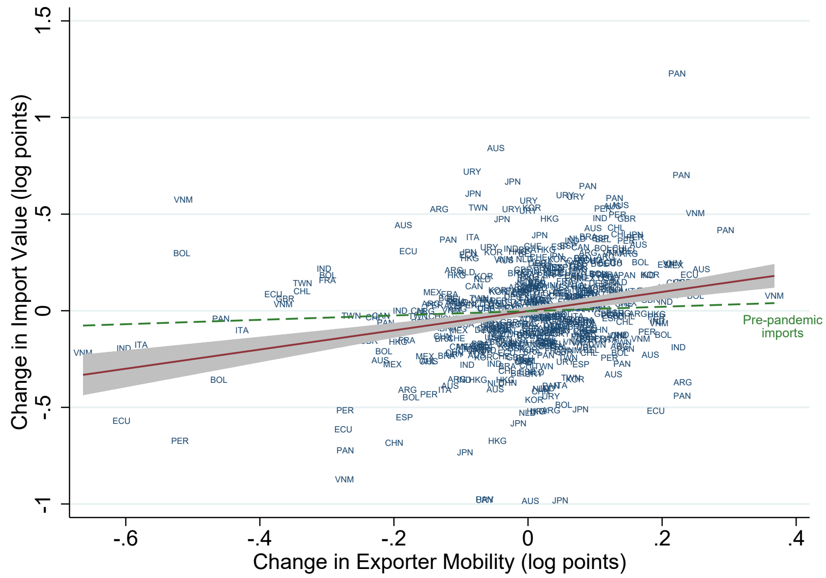
	(1)	(2)	(3)	(4)	(5)	(6)
Imports in the Pandemic period (2020-2021)						
Δ log Exporter Mobility (2020-2021)	0.337***	0.041	0.051	0.468***	0.081	0.101
	(0.050)	(0.053)	(0.056)	(0.058)	(0.063)	(0.068)
Country F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	32,380	32,380	32,380	32,380	32,380	32,380
R^2	0.004	0.010	0.011	0.018	0.023	0.024
Imports in the Pre-pandemic period (2018-2019)						
Δ log Exporter Mobility (2020-2021)	0.013	-0.031	-0.036	0.053	-0.003	-0.003
	(0.046)	(0.050)	(0.053)	(0.055)	(0.061)	(0.067)
Country F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	33,498	33,498	33,498	33,498	33,498	33,498
R^2	0.002	0.002	0.002	0.008	0.008	0.008

Note: OLS regressions at exporter location-time level, where time is at the monthly frequency. Fixed effects are included as indicated in each column. Robust standard errors clustered at the exporter-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

improve readability. In contrast to importer mobility shocks, we use time-series variation in this case, given the not inclusion of time fixed effects. Reductions in exporter mobility are associated with a reduction on exports to Colombia as expected.

In the bottom panel of Table B3, we conduct the same exercise as in the importer level section and regress changes in import values for 2018–2019 period relative to February 2018, i.e. before the pandemic, on changes in exporter mobility during the pandemic. We then estimate the same specifications as in the top panel. Reassuringly, all estimations are insignificant, which help us rule out the existence of pre-trends. Moreover, estimates that are insignificant in both cases —using either pre-pandemic or pandemic import changes as a dependent variable— are noisier when we use pre-pandemic import changes. In Figure B4 we also include the residual linear fit corresponding to Column (4) in the bottom panel of Table B4.

Figure B4: The Impact of Exporter Mobility on Import Values. Residual Plot



Note: Residual plot of equation 29 with country and month fixed effects (Column (4) of Table B4). Each observation is a country-time average of the residuals. Pandemic period fit (red solid line): $\hat{m}_{ct}^{resid} = -0.002 + 0.497{*}{*}{*} \times \hat{x}_{ct}^{I,resid}$. Pre-pandemic period (green dash line): $\hat{m}_{ct}^{resid} = -0.002 + 0.113 \times \hat{x}_{ct}^{I,resid}$.

In conclusion, mobility declines at the exporter location during the pandemic are associated with lower exports to Colombia as expected. Results are noisy when we only rely on cross-sectional variation, but still point in the same direction. Importantly, pre-pandemic changes are not associated with pandemic mobility shocks.

B.4 Robustness Exercises to Exporter-Importer-Product Level Local Shocks Results

Table B5: Local Importer and Exporter Mobility and Import Variables. Alternative Standard Errors Clustering.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log Import Value	Δ log Import Quantity	Δ log Import Price	Δ log Import Value	Δ log Import Quantity	Δ log Import Price
Δ log Importer Mobility	0.433***	0.410***	0.023	0.433***	0.410***	0.023
	(0.084)	(0.087)	(0.053)	(0.092)	(0.080)	(0.045)
Δ log Exporter Mobility	0.249**	0.352**	-0.103**	0.249**	0.352**	-0.103**
	(0.110)	(0.146)	(0.050)	(0.108)	(0.145)	(0.051)
Clustering	Exporting country-time and Importer location-time			Exporting country-time and Importer department-time		
N	537,100	537,100	537,100	537,100	537,100	537,100
R^2	0.100	0.101	0.076	0.100	0.101	0.076

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top of each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors clustered as indicated on the clustering row. *** p<0.01, ** p<0.05, * p<0.1

Table B6: Local Importer and Exporter Mobility and Import Variables. Congestion Controls.

	(1)	(2)	(3)
\textit{Dependent Variable}:	Δ log Import Value	Δ log Import Quantity	Δ log Import Price
Δ log Importer Mobility	0.397***	0.350***	0.046
	(0.073)	(0.073)	(0.052)
Δ log Exporter Mobility	0.404***	0.528***	-0.124***
	(0.094)	(0.124)	(0.045)
Congestion, demand side	-2.049***	-1.743***	-0.306
	(0.351)	(0.339)	(0.230)
Congestion, supply side	0.095	0.063	0.032
	(0.222)	(0.234)	(0.118)
N	486,090	486,090	486,090
R^2	0.106	0.107	0.080

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top of each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B7: Local Importer and Exporter Mobility and Import Variables. Interaction Term by Type of Goods.

	(1)	(2)	(3)
	Δ log value	Δ log quantity	Δ log price
Δ log Importer Mobility $\times$ Consumer	0.315**	0.209	0.107
	(0.152)	(0.164)	(0.084)
Δ log Importer Mobility $\times$ Intermediates	0.379***	0.313***	0.066
	(0.087)	(0.108)	(0.064)
Δ log Importer Mobility $\times$ Capital	0.392***	0.342***	0.050
	(0.119)	(0.130)	(0.068)
Δ log Exporter Mobility $\times$ Consumer	-0.439***	-0.388**	-0.051
	(0.131)	(0.154)	(0.080)
Δ log Exporter Mobility $\times$ Intermediates	0.197*	0.228*	-0.031
	(0.117)	(0.131)	(0.053)
Δ log Exporter Mobility $\times$ Capital	0.364**	0.148	0.216***
	(0.157)	(0.177)	(0.070)
Δ log Importer Mobility $\times$ Δ log Exporter Mobility $\times$ Consumer	-0.957***	-1.087***	0.131
	(0.252)	(0.273)	(0.122)
Δ log Importer Mobility $\times$ Δ log Exporter Mobility $\times$ Intermediate	-0.226	-0.448*	0.222**
	(0.214)	(0.260)	(0.109)
Δ log Importer Mobility $\times$ Δ log Exporter Mobility $\times$ Capital	0.035	-0.452	0.487***
	(0.263)	(0.341)	(0.148)
Observaciones	533,312	533,312	533,312
R^2	0.100	0.101	0.077

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top of each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B8: Local Importer and Exporter Mobility and the Extensive Margin.

	(1)	(2)	(3)
	Baseline	Congestion	Interaction
Δ log Importer Mobility	0.039***	0.036***	0.038***
	(0.005)	(0.006)	(0.005)
Δ log Exporter Mobility	0.021***	0.034***	0.019**
	(0.007)	(0.007)	(0.008)
Congestion, demand side		-0.082***	
		(0.017)	
Congestion, supply side		0.017*	
		(0.010)	
Interaction Exp x Imp Mobility			-0.003
			(0.017)
N	10,888,687	9,576,408	10,888,687
R^2	0.012	0.013	0.012

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable and interaction term indicated at the top of each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

B.5 Covid-Related Medical Goods

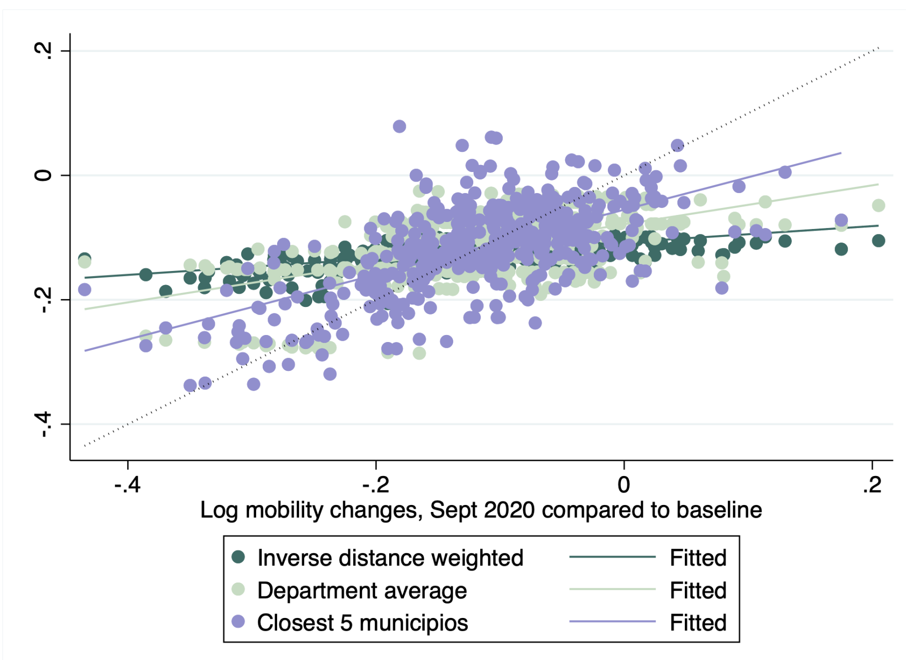
A list by World Customs Organization and World Health Organization specifies the list of Covid-related medical goods at HS6 level. They include the following sections: (1) COVID-19 test kits/instruments and apparatus used in diagnostic testing; (2) protective garments and the like; (3) disinfectants and sterilisation products; (4) oxygen therapy equipment and pulse oximeters; (5) other medical devices and equipment; (6) other medical consumables; (7) vehicles. Overall, these goods comprises about 7.7% of the total trade value.

These goods can be consumption goods, intermediate goods, or capital goods. Examples for consumption good include: men's protective garments made of rubberised textile fabrics, tents for setting up field hospitals, including temporary canopies, alcohol solution, undenatured, 75% ethyl alcohol. Examples for intermediate good includes laboratory, hygienic or pharmaceutical glassware, medical oxygen, hydrogen peroxide in bulk. Examples for capital good includes intubation kits, medical ventilators (artificial respiration apparatus).

We investigate the impact of importer shock and exporter shock on Covid-related medical supplies in Table 2, panel B. We find very intuitive results: lower importer mobility is associated with higher demand.

B.6 Importer Region vs Importer City

Figure B5: Regional mobility changes are highly correlated with city-level mobility changes in Colombia



B.7 Fixed Effect Averages for Baseline Regression

B.7.1 Quantity Equation

Figure B6: Sum of Country-Port-Time and Product-Time FE

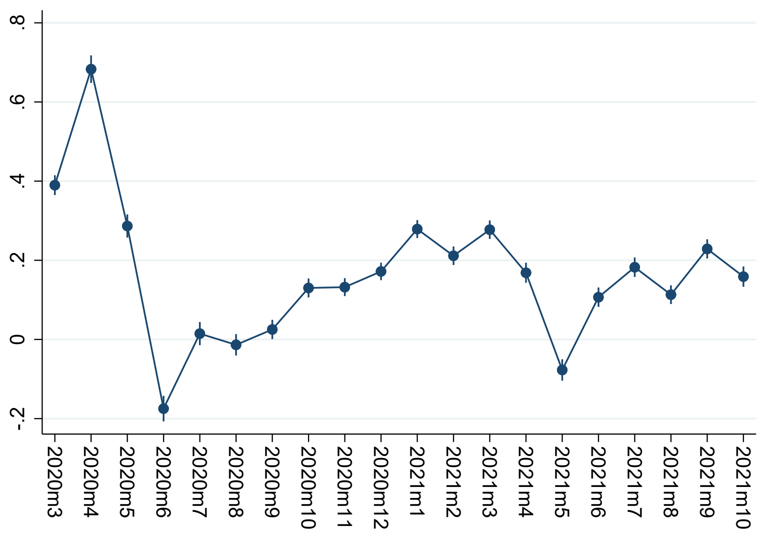


Figure B7: Country-Port-Time FE

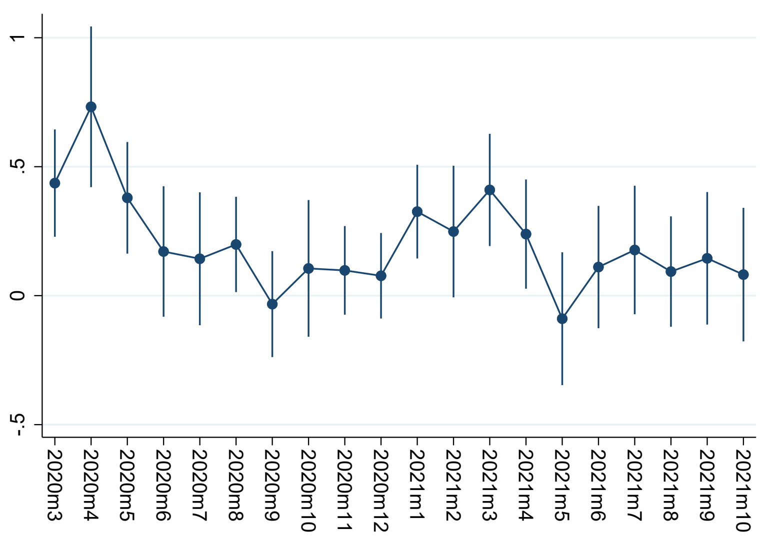
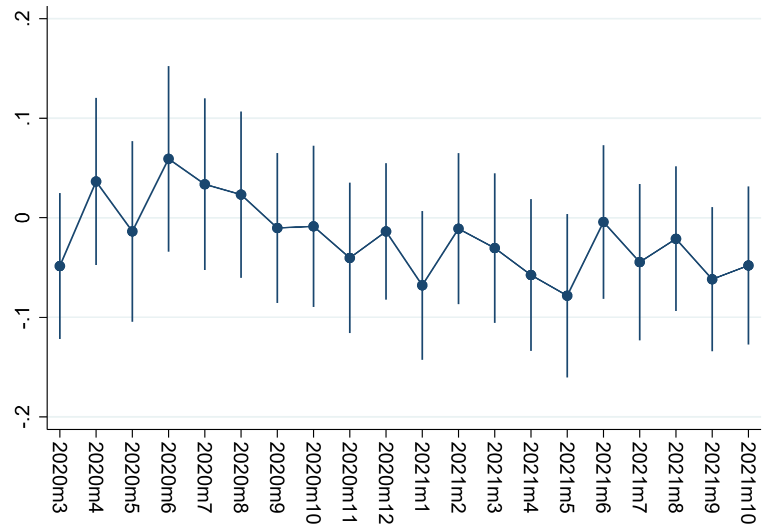


Figure B8: Product-Time FE



B.7.2 Price Equation

Figure B9: Sum of Country-Port-Time and Product-Time FE

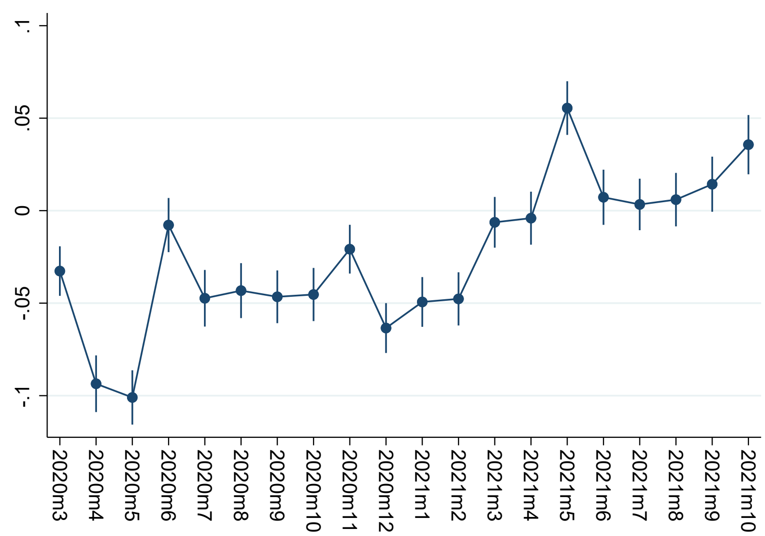


Figure B10: Country-Port-Time FE

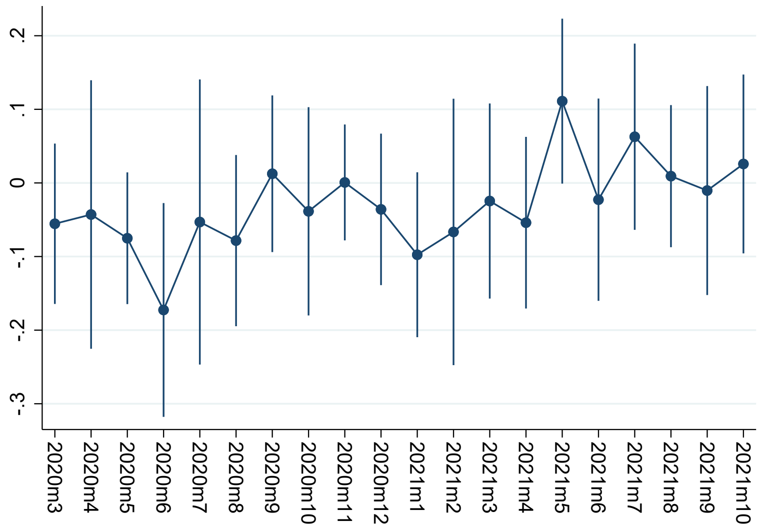
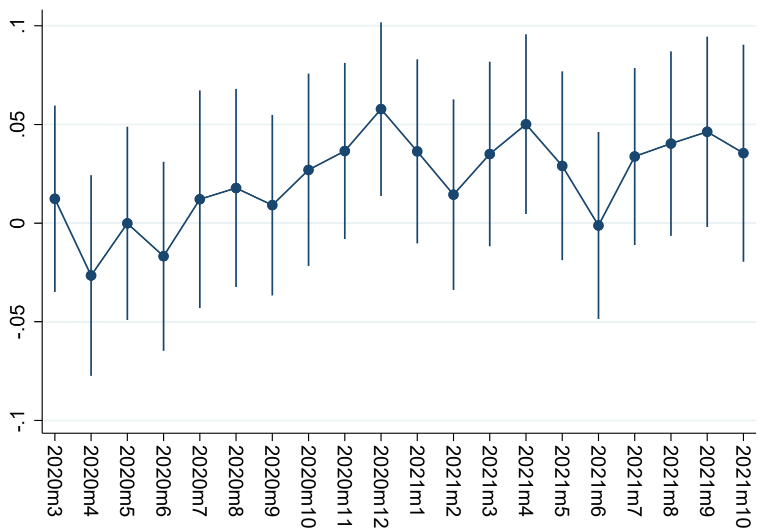


Figure B11: Product-Time FE



B.7.3 Correlation Between Country-Port-Time Fixed Effect (δ^{Tr}) and Country-Port-Time Observed Freight Unit Values Averages

Figure B12: Quantity Regression

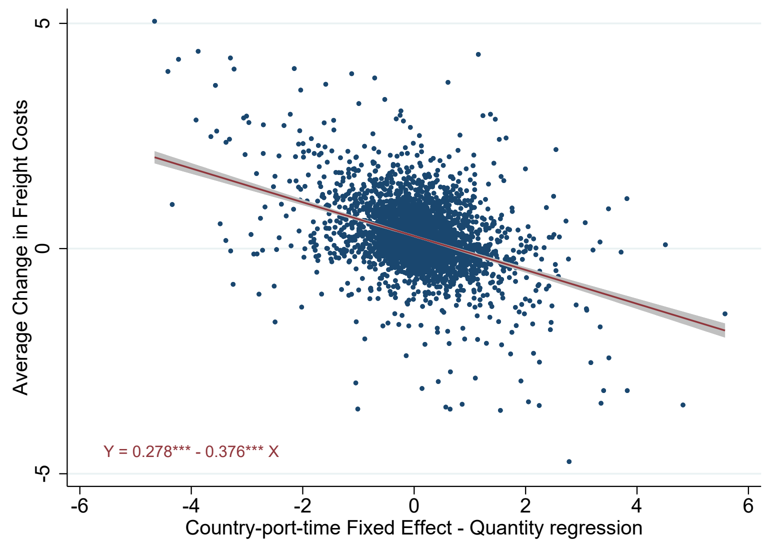
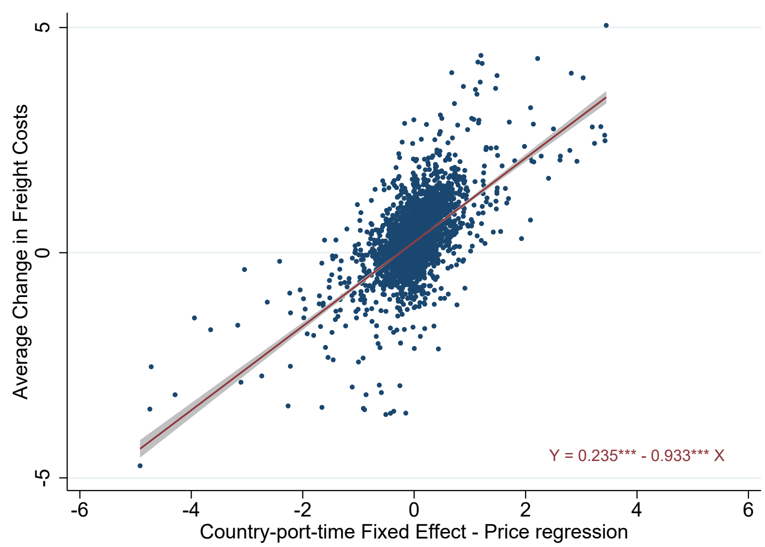


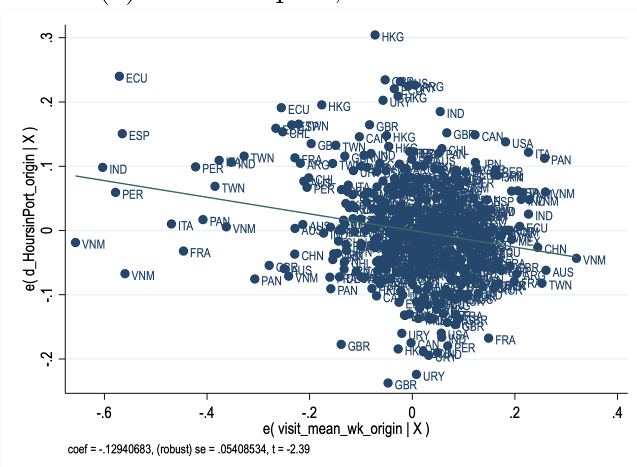
Figure B13: Price Regression



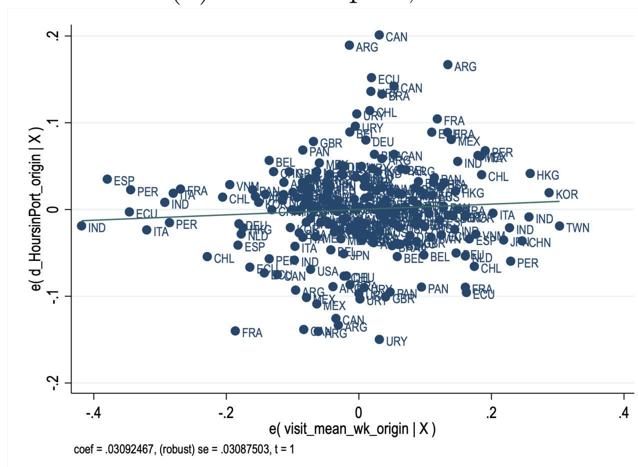
B.8 Country-Level Port Performance Results

Figure B14: The Impact of Mobility Changes on the Number of Hours in Port, Residual Plot for the Post-Covid period and the pre-Covid Period

(a) Hours in port, 2020 and 2021



(b) Hours in port, 2018



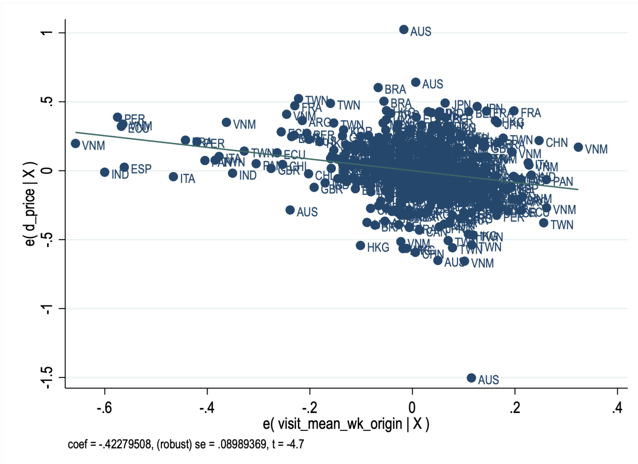
(c) Number of port calls, 2020 and 2021

(d) Number of port calls, 2018

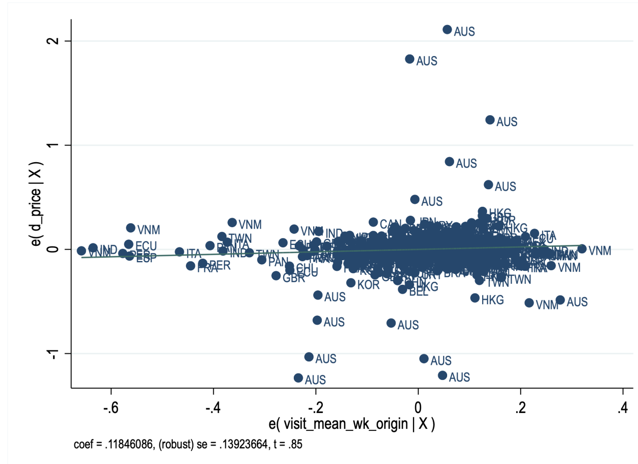
Note: Panel (a) is the residual plot for the results in Table 4 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 4 Column (3) in Panels A and in Panel B, respectively.

Figure B15: The Impact of Mobility Changes on the Freight Costs, Residual Plot for the Post-Covid Period and the Pre-Covid Period

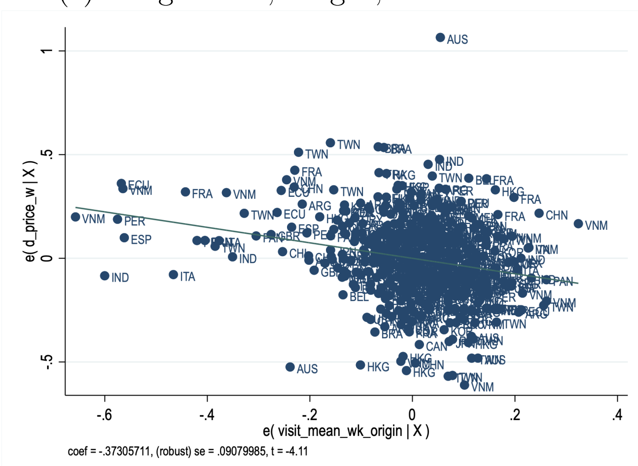
(a) Freight cost, unit, 2020 and 2021



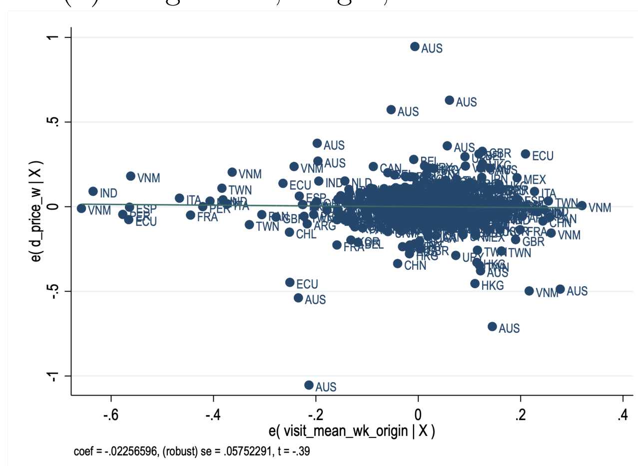
(b) Freight cost, unit, 2018 and 2019



(c) Freight cost, weight, 2020 and 2021



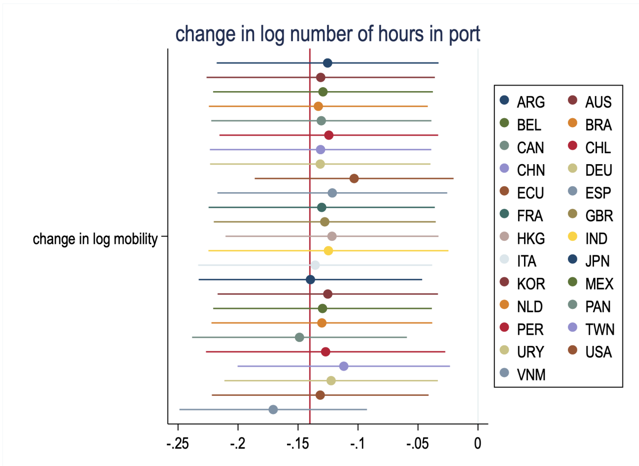
(d) Freight cost, weight, 2018 and 2019



Note: Panel (a) is the residual plot for the results in Table 4 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 4 Column (3) in Panels A and in Panel B, respectively.

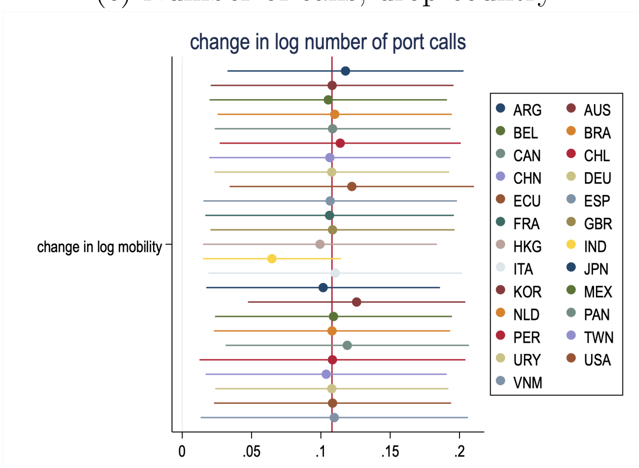
Figure B16: The robustness of country level results in Table 4, the impact of mobility changes on port performance, dropping one country at a time and dropping one period at a time

(a) Hours in port, drop country

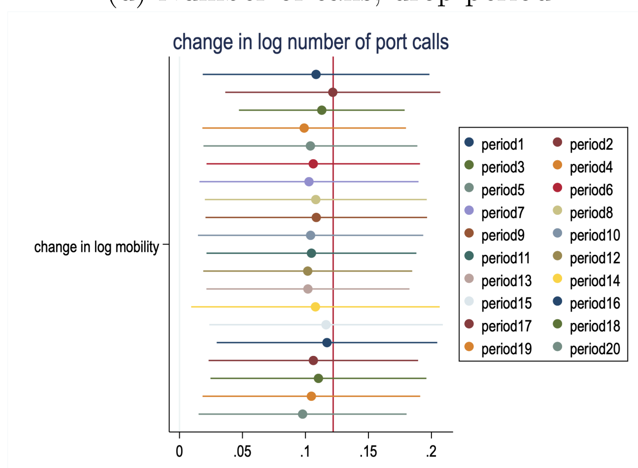


(b) Hours in port, drop period

(c) Number of calls, drop country



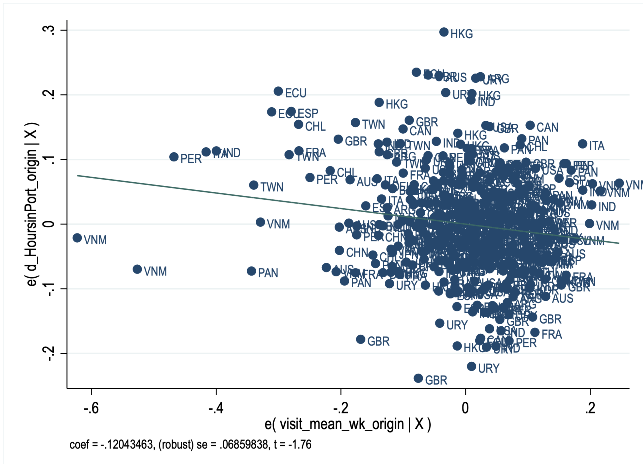
(d) Number of calls, drop period



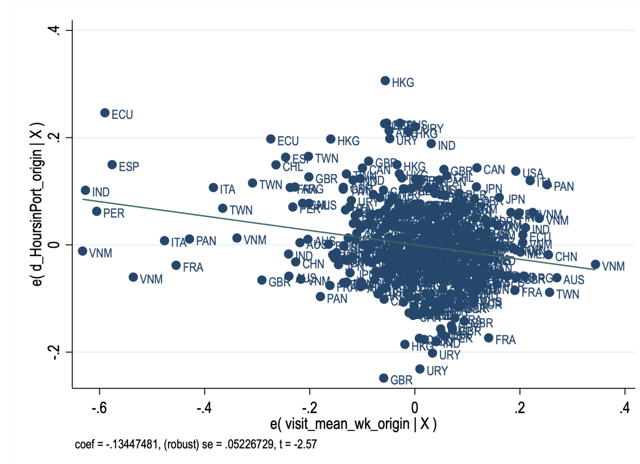
Note: Panel (a) plots the coefficients when replicating results in Table 4 Panel A Column (1) and dropping one country at a time, and Panel (b) plots the coefficients when dropping one period at a time. Panel (c) plots the coefficients when replicating results in Table 4 Panel A Column (3) and dropping one country at a time, and Panel (d) plots the coefficients when dropping one period at a time.

Figure B17: The robustness of country-level results, the impact of mobility changes on the number of hours in port, residual plot

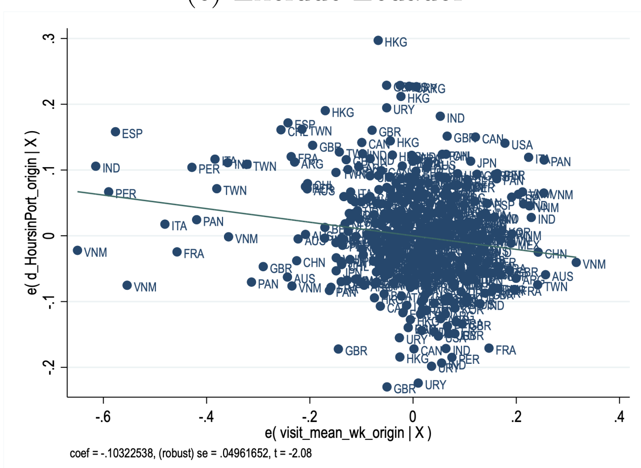
(a) Exclude March 2020



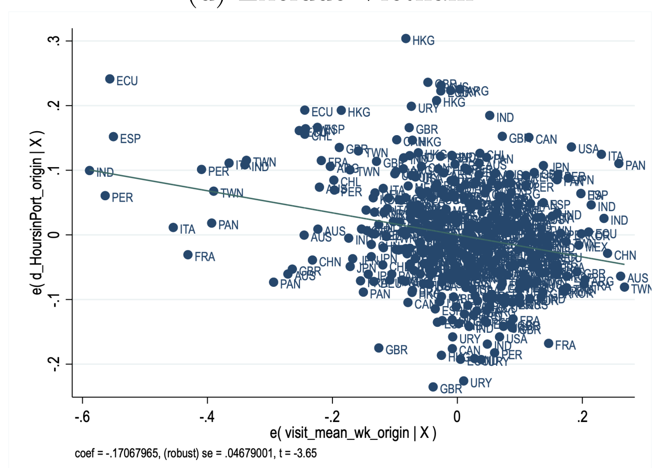
(b) Exclude April 2020



(c) Exclude Ecuador



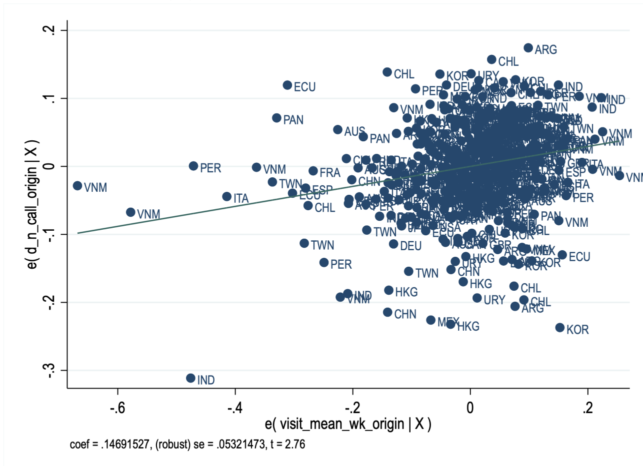
(d) Exclude Vietnam



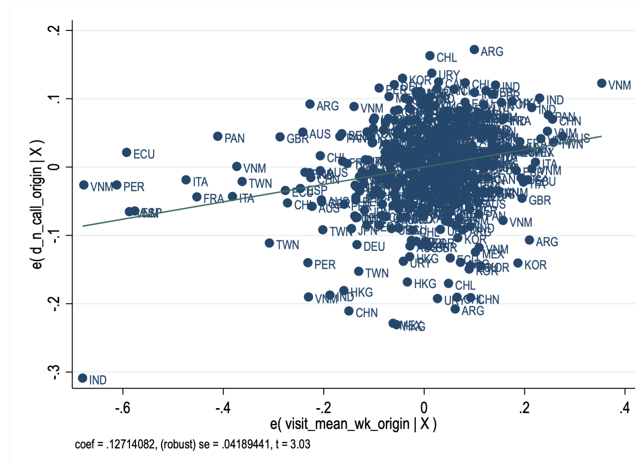
Note: Panel (a) is the residual plot for replicating results in Table 4 Panel A Column (1) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops Ecuador, and Panel (d) drops Vietnam.

Figure B18: The robustness of country level results, the impact of mobility changes on the number of port calls, residual plot

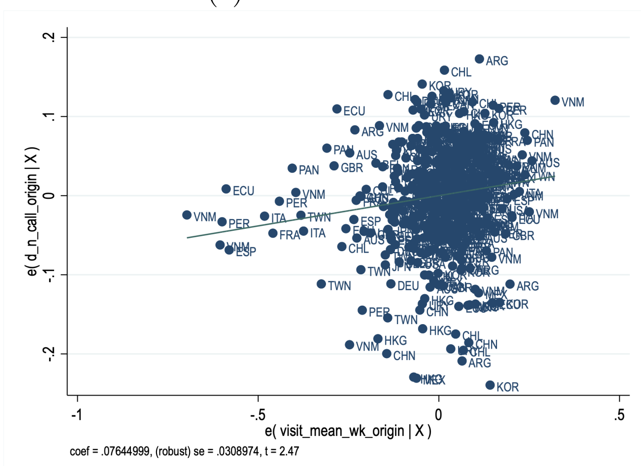
(a) Exclude March 2020



(b) Exclude April 2020



(c) Exclude India



(d) Exclude Vietnam

Note: Panel (a) is the residual plot for replicating results in Table 4 Panel A Column (3) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops India, and Panel (d) drops Vietnam.

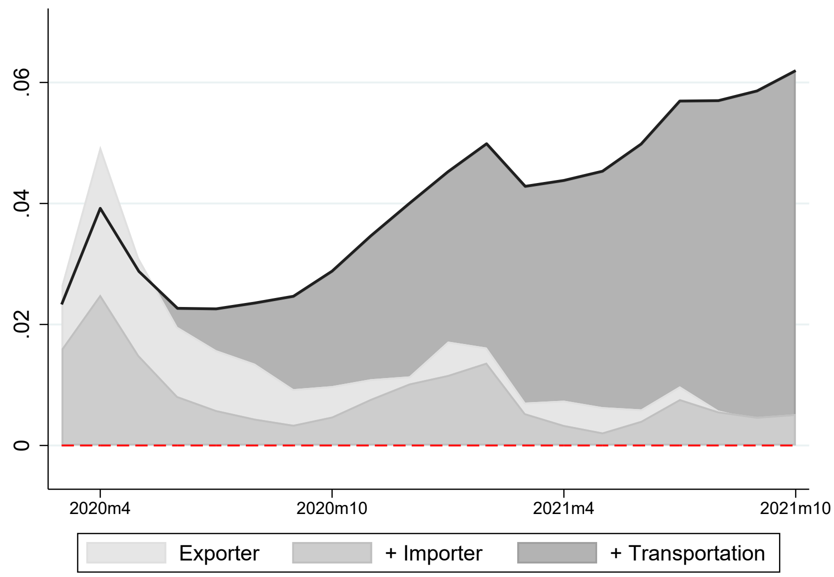
Table B9: The relationship between freight costs and mobility, without dropping the top 1% and the bottom 1%

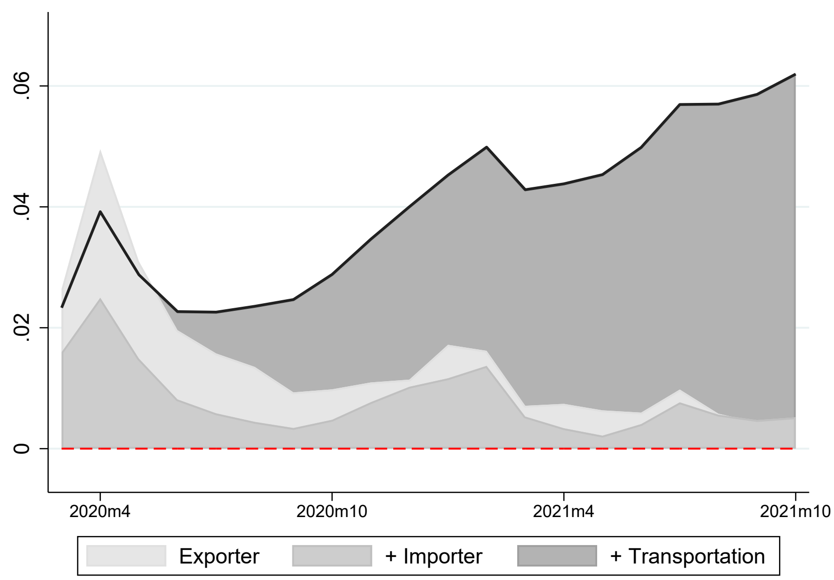
Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	-0.31**	-0.31**	-0.35***	-0.62***	-0.34***	-0.34***	-0.37***	-0.63***
	(0.11)	(0.11)	(0.12)	(0.21)	(0.10)	(0.10)	(0.11)	(0.17)
I (year=2021)	0.57***		0.57***	0.60***	0.60***		0.60***	0.63***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.05***				0.05***		
		(0.01)				(0.01)		
Constant	-0.02	-0.23***	-0.02	-0.08	-0.07	-0.29***	-0.07	-0.12**
	(0.05)	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
Observations	255,346	255,346	248,813	255,342	255,346	255,346	248,813	255,342
R-squared	0.12	0.12	0.16	0.12	0.15	0.15	0.19	0.16
Panel B.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2018 and 2019	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	0.05	0.02	0.04	0.03	-0.02	-0.00	-0.03	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
I (year=2019)	0.02*		0.03*	0.03**	0.03**		0.03**	0.03**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.02)
Time trend		0.00				0.00		
		(0.00)				(0.00)		
Constant	0.05***	0.04**	0.05***	0.04***	-0.02***	-0.03*	-0.02***	-0.03**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	271,942	271,942	265,877	271,942	271,942	271,942	265,877	271,942
R-squared	0.11	0.10	0.15	0.11	0.11	0.11	0.16	0.12
Month FE	Yes	Yes			Yes	Yes		
Product FE	Yes	Yes		Yes	Yes	Yes		Yes
Exporter country FE	Yes	Yes	Yes		Yes	Yes	Yes	
Product-month FE			Yes				Yes	
Country-month FE				Yes				Yes

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. The mean (s.d.) of the change in log freight cost by unit is 0.43 (1.62), and 0.36 (1.1) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country.

B.9 Additional Decomposition Results

Figure B19: Decomposition: Import Quantities and Prices of Consumer Goods

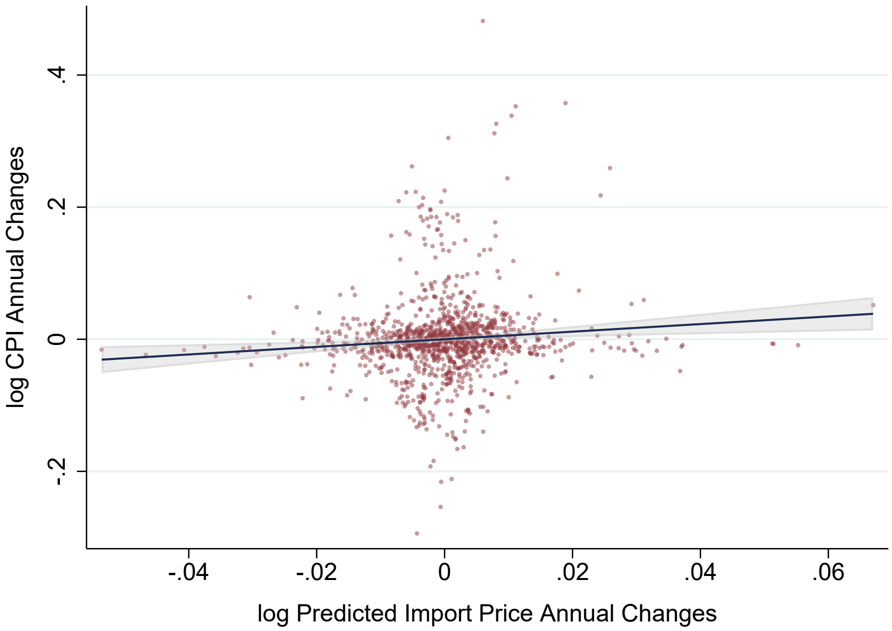




Note: Each data point is computed using baseline estimates for consumption goods in Table 2 and for freight costs in Table 5 and month-specific average changes in exporter, importer and port mobility.

B.10 Additional Inflation Results

Figure B20: Consumer Prices and Predicted Import Prices Changes due to Export Mobility Shocks



C Theory

C.1 Producer Problem

The representative firm selling k at i solves the following maximization problem:

$$\max_{\{p^X(j)\}\in\Omega^J} \int_{\Omega^J} p^X(j)q(j)dj - A\Big[\int_{\Omega^J} q(j)dj\Big]^\alpha$$

subject to $q(j) = (p^X(j)+t)^{-\sigma}(P^M)^{\sigma-1}Z(j)$, where I omitted subscripts i and k. The first order condition for $p^X(j)$ is as follows:

$$\begin{aligned}
q(j) + p^X(j)[-\sigma\frac{q}{p^M(j)}] - \alpha AC^{\frac{\alpha}{\alpha-1}}[-\sigma\frac{q}{p^M(j)}] &= 0 \\
-\frac{p^M(j)}{\sigma} + p^X(j) - \alpha AC^{\frac{\alpha}{\alpha-1}} &= 0 \\
-\frac{p^X(j)}{\sigma} - \frac{t}{\sigma} + p^X(j) - \alpha AC^{\frac{\alpha}{\alpha-1}} &= 0 \\
p^X(j)\frac{\sigma-1}{\sigma} &= \alpha AC^{\frac{\alpha}{\alpha-1}} + \frac{t}{\sigma} \\
p^X(j) &= \frac{\sigma}{\sigma-1}\alpha AC^{\frac{\alpha}{\alpha-1}} + \frac{1}{\sigma-1}t
\end{aligned}$$